Worker Displacement in Appalachia:

Using Detailed Industry and Firm Data to Link the Displaced Worker Supplement to Appalachia

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Report Overview

Worker displacement — the separation of a worker from their employer in a way that is involuntary, permanent, and independent of on-the-job performance — is a concern to policymakers because of negative long-term impacts on employment and earnings. This report examines worker displacement in the Appalachian Region, analyzing effects on workers in Appalachia and comparing those to the experiences of workers in the non-Appalachian United States.

The report analyzes data from the Displaced Worker Supplement (DWS), a biennial national survey that has provided information on the causes of displacement and short- and long-term effects on workers since 1984. The DWS gathers information on workers who are civilians at least 20 years old and asks about job displacement over the previous three calendar years. Displaced workers are "long-tenure" workers who had worked at least three years in the job from which they were displaced. The survey tracks displacement resulting from plant closures or moves (Type 1), insufficient work (Type 2), or the elimination of a position or shift (Type 3). In addition, the survey includes information on demographic factors including age, sex, race/ethnicity, and educational attainment, as well as work-related conditions such as industry and occupation, job tenure, and previous and current earnings. The five most recent iterations of the DWS (data covering the 2011-2021 period) are analyzed in this report, along with some comparisons to earlier time periods.

In addition to providing an updated analysis of worker displacement in the Appalachian Region using the DWS, this report also explores the potential for new estimation methods to generate higher-quality information on displacement in Appalachia. Specifically, this report utilizes industry-based approaches to estimate the portion of national displacement occurring within the region's 423 counties. These county-level estimates provide reliable benchmarks, help explain the geography of displacement, and identify drivers of displacement within Appalachia.

This report is organized into four primary sections:

1. **Literature review** — This section examines relevant literature on worker displacement, including past research on factors contributing to displacement, patterns and trends in the demographics of displaced workers, and the impacts of displacement.
2. **Analysis of the DWS** — This section analyzes data from the DWS, providing insights on worker displacement in the Appalachian Region and how it compares to displacement taking place in the non-Appalachian United States. The experiences of displaced workers are broken down by both demographic and work-related factors.
3. **Industry-based approach** — This section introduces a novel industry-based approach to estimate worker displacement at the county-level throughout Appalachia. The section also estimates the impacts of Type 1 displacement (plant closures and moves), and identifies the industries most likely to have closed or moved out of the region.
4. **Characteristics of displaced workers** — This section analyzes the characteristics and experiences of displaced workers in the Appalachian Region and across the U.S.

The report also contains a brief conclusion and multiple appendices that provide additional data and methodological details for interested parties.

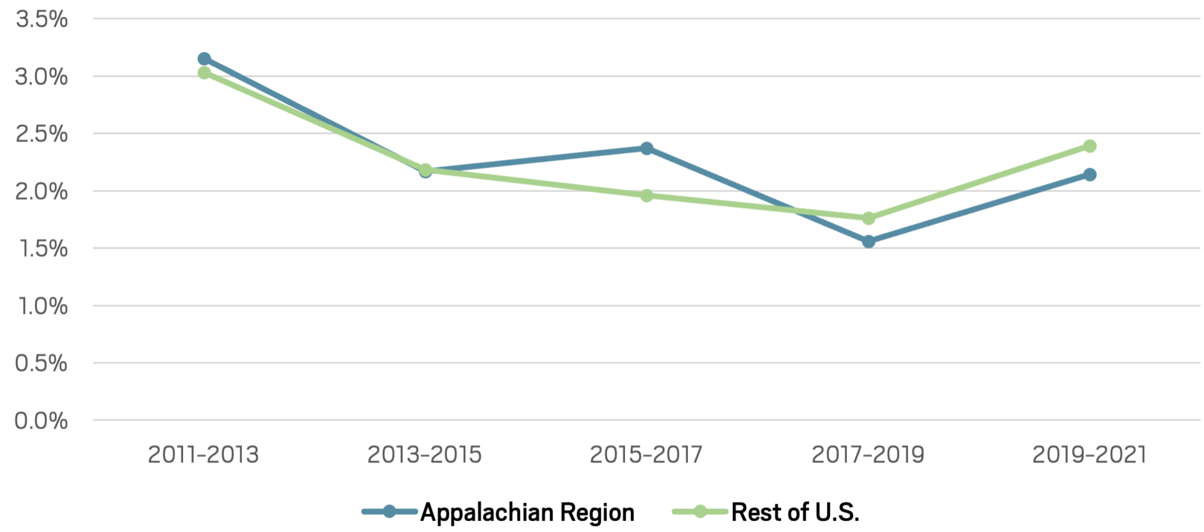
Key Findings

#1. Worker displacement is trending downward in the Appalachian Region.

In the Appalachian Region, displacement rates, which capture the proportion of the workforce that has been separated from a long-tenure job in the prior three years, have been trending downward over the past decade. The highest displacement rate for Appalachian workers was recorded in the first survey period (3.2% in 2011-2013), while the two lowest rates were recorded in the last two survey periods (1.6% in 2017-2019 and 2.1% in 2019-2021). Displacement rates in the rest of the U.S. also showed a downward trend over the decade—though, as in Appalachia, there was slight increase in displacement rates between the 2017-2019 and 2019-2021 survey periods (from 1.6% to 2.1% in Appalachia, and from 1.8% to 2.4% in the rest of the U.S.).

Displacement rates in Appalachia also show evidence of a longer-term decline, averaging only 2.3% in the five surveys covering 2011-2021 compared to 3.3% in the 1993-2003 period. An almost identical long-term trend is apparent in the rest of the U.S., where displacement rates declined from 3.2% in 1993-2003 to 2.3% in the 2011-2021 period.

Figure I. Displacement Rates in the Appalachian Region and the Rest of the U.S., 2011-2021



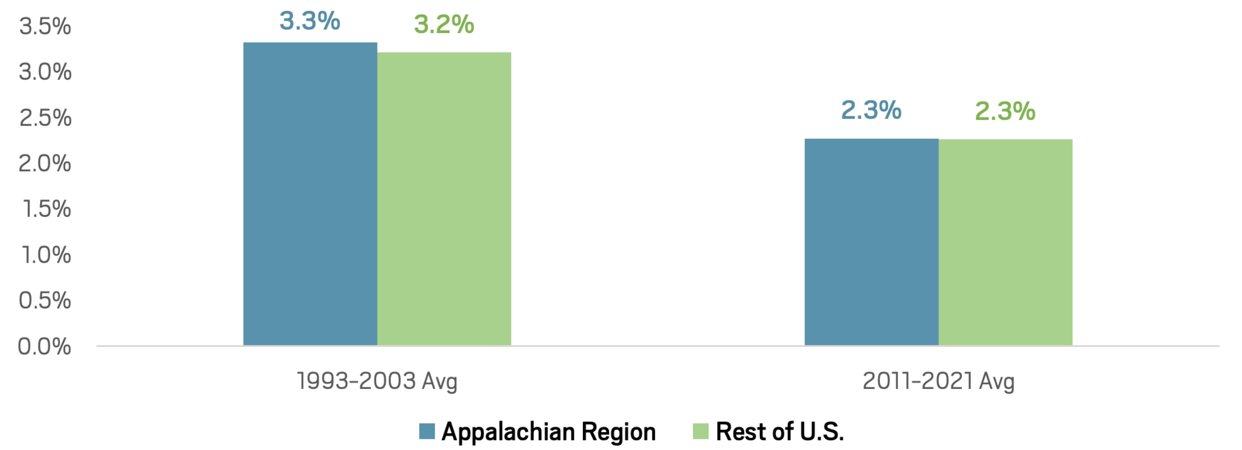
Source: CPS DWS; Mass Economics analysis.

#2. Displacement rates in the Appalachian Region are similar to rates in the rest of the United States.

Over the five surveys covering the years 2011 to 2021, the average displacement rate in both Appalachia and the rest of the U.S. was 2.3%. Rates in Appalachia were higher than the national average in two surveys, identical (to one decimal place) in one survey, and lower in two surveys. Compared to this more recent 2011-2021 period, displacement rates over the 1993-2003 period were higher for both Appalachia (3.3%) and the rest of the U.S. (3.2%).

A key reason why worker displacement rates in the Appalachia Region are similar to rates for the rest of the country is that the geographies have similar proportions of employment in high-displacement industries. With the exception of distressed counties, where workers are more likely to be employed in industries with higher-than-average displacement rates, the Appalachian Region's employment mix resembles that of the rest of the U.S. in terms of displacement risk. Industry dynamics and employment trends over recent decades have contributed to this similarity between Appalachia and the rest of the country; industries with higher-than-average displacement rates (e.g., mining) employ fewer workers today in Appalachia than in previous decades.

Figure II. Average Displacement Rates in the Appalachian Region and the Rest of the U.S., 1993-2003 and 2011-2021



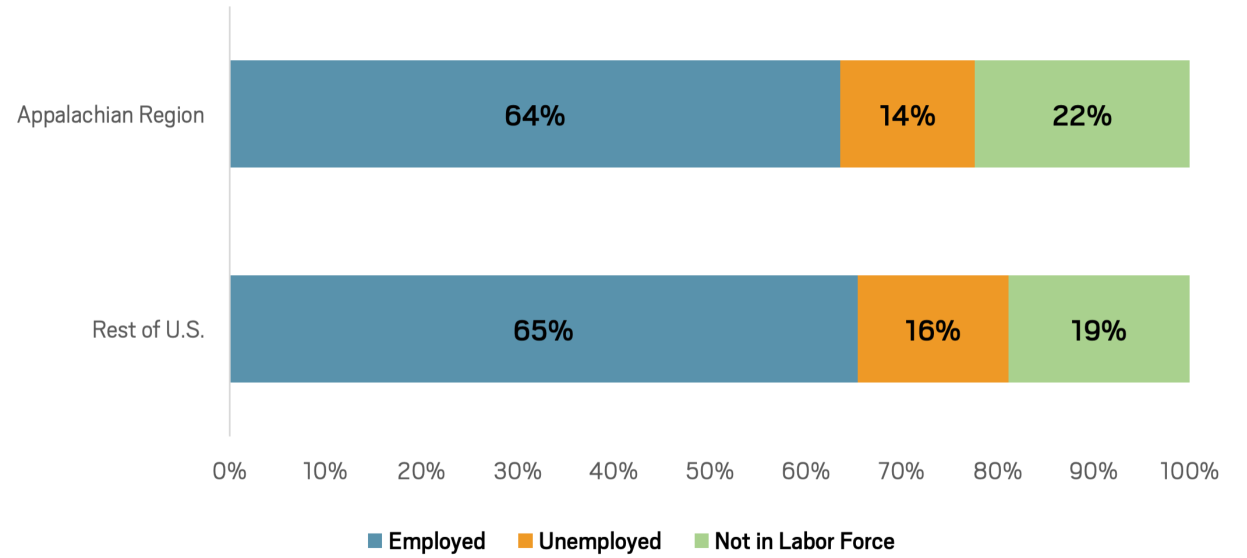
Source: CPS DWS; Mass Economics analysis.

#3. In the Appalachian Region and across the U.S., displacement can lead to long-term joblessness and/or exiting the labor force.

Almost one in three displaced workers report that they had not worked since being displaced from their jobs. These rates were almost identical for workers in Appalachia (32%) and those in the rest of the U.S. (31%). Among workers who were able to find employment after being displaced, 20% of those workers in Appalachia and 24% of those outside the region reported that they had gone over six months (27 weeks or longer) before starting their next job. About 9% in both geographies report that they had not worked for at least a year between displacement and their next job.

For many workers, displacement leads to detachment from the labor force. This is especially true in rural areas: 26% of displaced workers in nonmetro Appalachia report "not in the labor force" as their current status compared to only 20% of workers in metropolitan parts of the Appalachian Region. A similar though somewhat smaller gap exists for displaced workers in the rest of the U.S. where 18% of displaced metropolitan workers were no longer in the labor force compared to 22% of those in nonmetropolitan areas. Among workers in the Appalachian Region, about 14% were unemployed at the time of being surveyed, a rate that was identical in metro and nonmetro areas.

Figure III. Current Labor Force Status Among Displaced Workers, 2011-2021



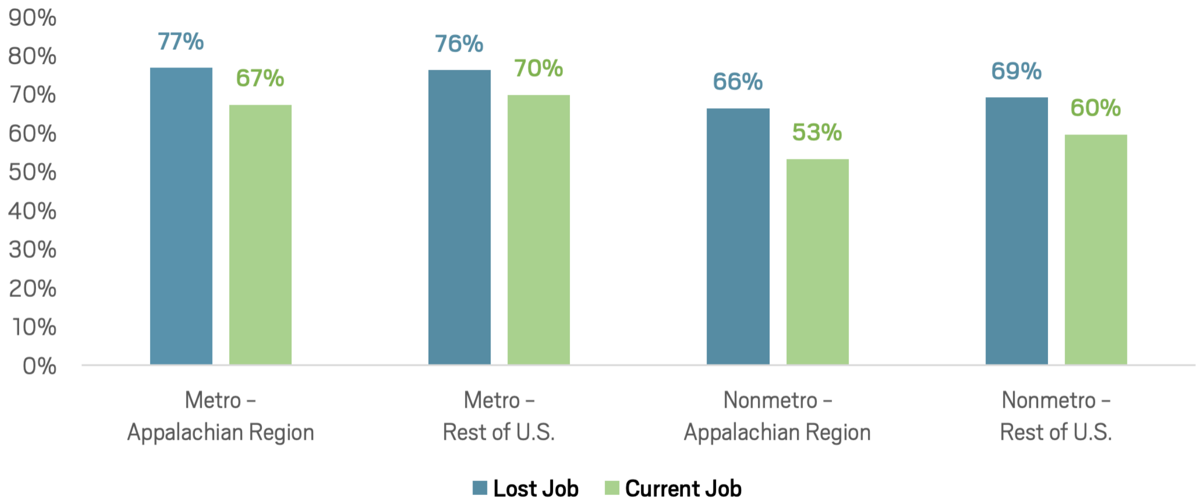
Source: CPS DWS; Mass Economics analysis.

#4. Displaced workers who find new jobs often experience a decline in earnings.

Among residents of the Appalachian Region who report both current and previous earnings, there is a significant decline in the proportion of workers who make more than $600 per week after being displaced and re-employed. The drop-off is larger in Appalachia than in the rest of the U.S., for both metro and nonmetro workers. Among all workers in the Appalachian Region, 73% report making more than $600 at the job from which they were displaced, whereas only 62% report making that at their current job. Workers outside of Appalachia also report a decline in earnings, though the percentage of workers that experienced a decline is lower outside of the region (75% of workers in the rest of the country made more than $600 at the job from which they were displaced, compared to 68% at their current job).

Earnings losses among rural workers in Appalachia are far more dramatic with 13% of displaced workers in nonmetro Appalachia going from more than $600 in weekly earnings at the job from which they were displaced to less than $600 at their current job (66% versus 53%). Moreover, about one-quarter (26%) of displaced nonmetro Appalachian workers report making less than $400 per week, significantly higher than the 17% of workers who made this wage at their lost jobs.

Figure IV. Percent of Displaced Workers Making at Least $600 per Week, 2011-2021



Source: CPS DWS; Mass Economics analysis.

#5. Displacement rates in Appalachia vary by worker characteristics and geography.

Over the 2011-2021 period, some groups of workers were more susceptible to displacement than others. Differences in age, education level, and industry type affected the rates of displacement among workers from both metro and nonmetro parts of Appalachia. Among workers 55 and older, 3.1% experienced displacement during the decade compared to only 1.4% of workers in the 20-34 age group. Less educated workers also experienced higher levels of displacement, with 2.6% of workers without a high school diploma affected compared to 2.4% of high school graduates and only 1.9% for workers with at least a Bachelor's degree. These differences are similar to those reported in the last analysis of displacement in the Appalachian Region, which covered data from 1993 to 2003.

The difference in displacement rates between goods-producing industries and service industries has declined over time. In surveys covering the 1993-2003 period, displacement rates in goods-producing industries, such as manufacturing and mining, were about 3.0 times higher than displacement rates in service industries. In surveys for the 2011-2021 period, this difference declined to about 1.4 times higher.

Although overall displacement rates for metro and nonmetro Appalachian workers were nearly identical, data show that nonmetro workers without a high school diploma, and those who work in goods-producing industries, had higher displacement rates compared to those in metro areas. Workers with less than a high school diploma in nonmetro areas had an average displacement rate of 3.2% in the 2011-2021 period, compared to 2.2% of similar workers in metro areas. Among workers in goods-producing industries, 3.3% of those living in nonmetro areas were displaced, compared to 2.7% in metro areas.

Table I. Displacement Rates by Appalachian Region Metro/Nonmetro, 2011-2021

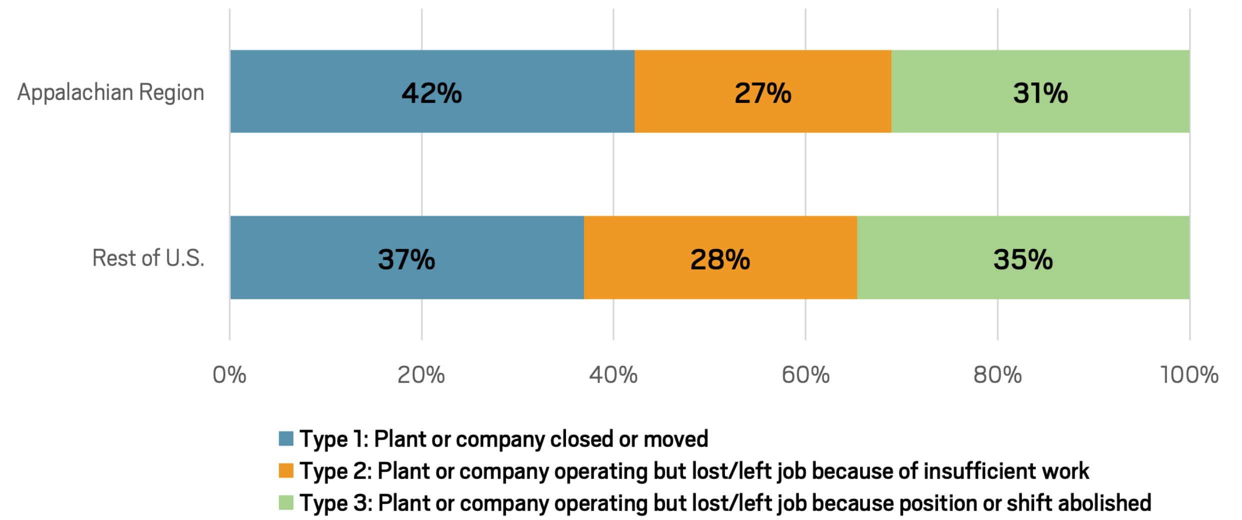
	APPALACHIAN REGION			
	Total	**Metro**	**Nonmetro**	**Metro-Nonmetro, % Point Delta**
All	2.3%	2.2%	2.3%	-0.1%
Gender				
Female	2.1%	2.1%	2.0%	0.1%
Male	2.4%	2.4%	2.6%	-0.2%
Age				
20-34	1.4%	1.4%	1.3%	0.1%
35-54	2.4%	2.3%	2.6%	-0.4%
55+	3.1%	3.3%	2.8%	0.4%
Education				
Less than High School	2.6%	2.2%	3.2%	-1.0%
High School	2.4%	2.4%	2.5%	0.0%
Some College or Associate's Degree	2.4%	2.6%	2.1%	0.4%
Bachelor's Degree or Higher	1.9%	1.9%	2.0%	-0.1%
Race				
White, non-Hispanic	2.4%	2.4%	2.4%	0.0%
People of Color	1.9%	1.9%	1.8%	0.1%
Industry (excl. public admin, gov)				
Goods-Producing	3.0%	2.7%	3.3%	-0.6%
Services	2.1%	2.2%	2.0%	0.2%

Note: Because of rounding, deltas may not match those calculated from table values.
Source: CPS DWS; Mass Economics analysis.

#6. Displacement in Appalachia is often due to plant closures and moves.

Forty-two percent of displacement in the Appalachian Region in the 2011-2021 period was due to plant closures and moves (Type 1), compared to 37% in the rest of the U.S. These rates are even higher in the nonmetro areas of Appalachia, where 48% of displacement is Type 1, compared to only 39% of displacement in metro Appalachia. Displacement due to insufficient work (Type 2) accounts for an almost identical proportion of total displacement in the Appalachian Region (27%) and the rest of the U.S. (28%). Type 3 displacement (elimination of a position or shift) is less common in the Appalachian Region (31%) than in the rest of the U.S. (35%).

Figure V. Type of Displacement, 2011-2021



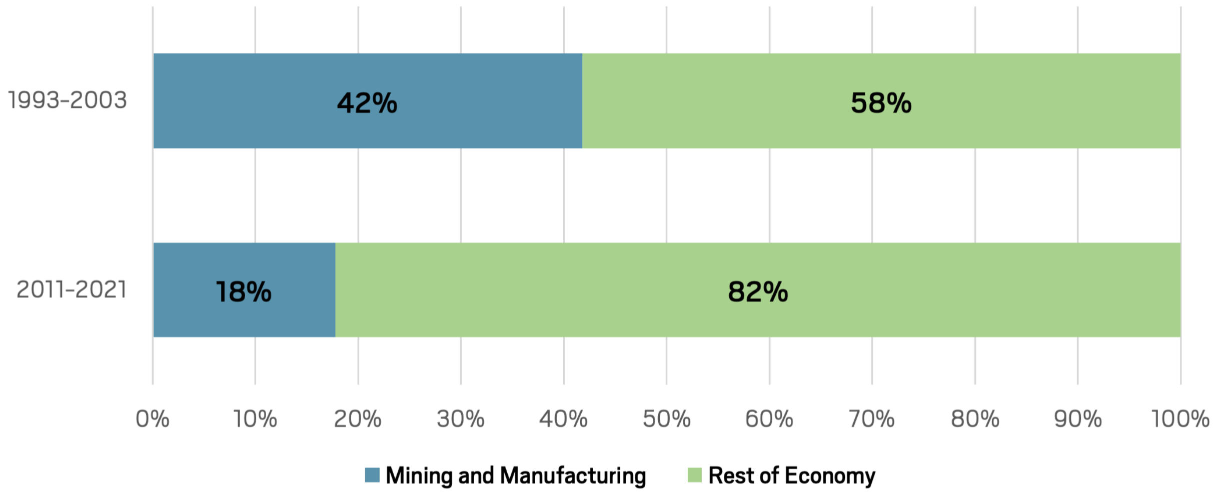
Source: CPS DWS; Mass Economics analysis.

#7. The industries driving displacement have changed over time.

Across the US economy, there are long-term trends in the type of industries that drive displacement as well as considerable variability from survey to survey, reflecting shorter-term influences in the economy. For example, the declining contribution of manufacturing and mining to total national employment is reflected in the displacement rates, as well: in the five surveys covering 1993 to 2003, manufacturing and mining accounted for almost 42% of all displacement, compared to 18% in the surveys covering 2011 to 2021. The shocks from the COVID pandemic and aftermath, on the other hand, created some unique conditions in 2019-2021: three of the industries with the highest number of displaced workers in the survey covering those years — Amusement, Gambling and Recreation; Management, Scientific, and Technical Consulting; Outpatient Care Services — are not substantial contributors to displacement in any other survey in that decade.

Two factors drive the contribution of industries and sectors to worker displacement: the rate of displacement and the number of employees associated with the industries and sectors. In terms of displacement rates, across the five surveys covering 2011 to 2021, only two industries — Coal Mining and Other Information Services — have one of the five highest displacement rates in multiple surveys (and in both cases, only two surveys). In terms of absolute displacement, only five industries rank in the top 10 industries with the most displaced workers in every survey covering 2011 to 2021: Construction; Restaurants and Food Services; General Medical, Surgical, and Specialty Hospitals; Elementary and Secondary Schools; and Computer Systems Design.

Figure VI. Share of Displaced Workers by Industry Segment, 1993-2003 and 2011-2021



Source: CPS DWS; Mass Economics analysis.

1. INTRODUCTION

1.1 Overview

This report builds on and extends prior analyses of worker displacement in Appalachia, as captured in the Current Population Survey's Displaced Worker Supplement (DWS).[1] Observations in the DWS survey are coded for geography, but those geographies do not necessarily align with the boundaries of the Appalachian Region, which is defined at the county level.[2] Some survey observations, so-called "partial geographies," map to geographic areas which are partly within, and partly outside of, the Appalachian Region. Earlier work uses workforce characteristics and logit models to estimate the Appalachian share of displacement within these partial geographies. In this work, we replicate this approach, then develop industry-based methods that leverage other sources of public and private data related to displacement.

The purpose of this work is to provide a detailed analysis of worker displacement within and across the Appalachian Region over the past decade using information from the DWS to estimate the rate of displacement in different periods and capture how experiences of displaced workers vary across different dimensions (e.g., industry, worker demographics and other characteristics, etc.). Using high-quality, localized industry data allows for more geographically detailed analyses, and provides greater information on the underlying industry drivers leading to different types of displacement events.

1.2 Motivation

The main goal of this work is to provide an updated analysis of worker displacement in the Appalachian Region. However, this work also provides an opportunity to explore whether new data and methods can improve the depth and breadth of understanding of worker displacement and, in the process, address some of the limitations associated with national and sub-national analyses of displacement using the DWS, a survey-based dataset that covers about 60,000 households and organizes respondents into observations with limited geographic detail.[3]

In developing an industry-based approach to worker displacement, the project team aims to avoid the geographic limitations inherent in the DWS by using other public and private data sources to estimate

1. See: Herzenberg, Stephan, Mark Price, and Howard Wial. n.d. "Displacement in Appalachia and the Non-Appalachian United States, 1993- 2003: Findings Based on Five Displaced Worker Surveys." Keystone Research Center. https://arc.gov/wp- content/uploads/2005/12/DisplacementAppalachiaandNonAppalachianUS1993to20031.pdf.

2. See https://www.arc.gov/appalachian-counties-served-by-arc/ for a map and list of the counties within the Appalachian Region.

3. Across the five survey years in question – 2014, 2016, 2018, 2020, and 2022 – about 41% of all DWS observations and about 44% of observations reflecting displaced workers report county FIPS information.

displacement at the county level. These estimates will provide reliable benchmarks, help explain the geography of displacement, and identify drivers of displacement across and within the Appalachian Region.

1.3 Guide to this Report

Following the sequence of the analysis, this report is broken into four primary sections:

Section 2 provides an overview of the current landscape of worker displacement literature, including discussion of: the factors contributing to displacement (subsection 2.2), patterns and trends in the demographics of displaced workers (2.3) and the outcomes and impacts of displacement (2.4), and, lastly, the primary data sources used to study displacement (2.5).

Section 3 details the data sources and methods to replicate the approach by Herzenberg, Price, and Wial (2005) and apply to five recent years of DWS data (2014, 2016, 2018, 2020, and 2022). Subsection 3.4 contains some of the key findings from the analysis, including discussion of displacement trends over time, geography (e.g., within the Appalachian Region vs. the rest of the U.S.), industry, and by displaced worker demographics.

Section 4 introduces two new industry-based approaches to estimating displacement in the Appalachian Region. The first is similar to the previous study's methodology but uses geography- and industry-specific data on separations and hires of workers instead of worker characteristics. The second approach — termed the "industry mix" approach — leverages detailed, county-specific industry data to estimate displacement and is unique in its geographic resolution of displacement (i.e., down to the county level). After discussion of data sources and methodologies, the results, strengths and weaknesses of all three methods are compared (subsections 4.9 and 4.10).

Section 5 first analyzes the characteristics and experiences of displaced workers in the Appalachian Region, the rest of the U.S., and the metro and nonmetro portions of the Appalachian Region and rest of U.S. using detailed variables present in the DWS (subsection 5.3). Next, using a new, industry-based approach, profiles of the displaced workers and disparities across different demographic groups (i.e., age, gender, race/ethnicity, educational attainment) and industry sectors are summarized within the Appalachian Region, the rest of the U.S., and down to the county level (subsection 5.4).

Concluding remarks and references are included in sections 6 and 7, respectively. Sections 8-10 reflect appendices with additional methodological details for interested parties.

2. LITERATURE REVIEW

2.1 Overview of Worker Displacement

Worker displacement refers to the separation of a worker from their employer in a way that is "involuntary," "permanent," and without recall, and independent of their on-the-job "performance" or capabilities (Abbott 2008). Research on displacement typically identifies three types of displacement events: worker separations for long-tenured workers — those who have been employed by the same employer for at least three years — resulting from a plant or facility closing or moving ("Type 1"), insufficient work or a reduction in work hours ("Type 2"), or the elimination of a position or shift ("Type 3") ("Current Population Survey, January 2022: Displaced Worker, Employee Tenure, and Occupational Mobility Supplement File" 2022).[4] Long-tenured workers are the subject of most displacement analyses because they are often thought to be the most vulnerable to displacement events and face potentially irreparable damage to their employment and earnings trajectories (Abbott 2008; Helwig 2001).[5] It is worth noting that older definitions of displacement have also implied that displaced workers will have trouble finding re-employment, especially in a related industry (Flaim and Sehgal 1985; Esposito 1999). While this review does not assume inevitability of re-employment challenges, it discusses re-employment challenges as a common, often-unavoidable outcome of displacement.

2.2 Factors Contributing to Displacement

Though there is generally a dearth of research on the underlying causes of worker displacement (Abbott 2008), worker displacement is often attributed to a combination of macroeconomic and microeconomic factors.[6] These factors can be categorized as technological, demand-side and supply-side factors.

4. This follows the definition from the Displaced Worker Supplement (DWS), an addition to the Current Population Survey (CPS). The universe of workers only includes those that are at least 20 years old.

5. Long-tenured workers are generally older and higher-earning, and have worked long enough at the same employer to have cultivated a strong relationship with them and their industry. Examining only long-tenured workers helps reduce (or eliminate) confounding effects from poor employee-employer "match" (e.g., skills, industry, work environment) (Herzenberg, Price, and Wial 2005). But this preference for studying long-tenured workers leaves an obvious gap when it comes to understanding the impacts of job displacement on shorter- tenure workers, as past research has pointed out (Kletzer and Fairlie 2003), especially as this group could make up half of all displaced workers (Bolle 1993).

6. To some extent, displacement events such as plant closures may also be "cause and consequence" of these broader economic factors (Howland 1988).

Technological factors refer to the adoption of new technologies by firms, including digital transformations such as incorporating artificial intelligence, using robotics, or leveraging cloud-based services, among countless others. These factors are top of mind in today's public discourse on worker displacement. For example, given the wide variation in automation potential by industry sector and occupation (Manyika et al. 2017), the breadth and severity of displacement events from automation are likely to vary from place to place. However, while recent studies have shown that artificial intelligence's adoption can produce a "displacement effect," there is also a "productivity effect" that generates "demand for labor in non-automated tasks" (Acemoglu and Restrepo 2018). Furthermore, a recent case study on a multinational insurance company suggests that digital transformation may not displace jobs but eliminate or transform tasks.

Individual tasks on their own can be easy to automate, but it becomes increasingly more challenging to automate the numerous combinations of tasks for which a single job may be responsible. The company profiled in the case study also experienced downsides to adopting an entirely new technology system, as these types of outright technology replacements pigeon-holed the company into more rigid systems (Reynolds, Brown, and Ryan 2021).

Demand-side factors, such as trade and recessions, affect customers' ability to purchase (and interest in purchasing) goods and services. For example, losing a significant customer could suddenly halt the company's production lines if the firm does not have enough working capital to continue operating. These factors are hugely impactful for a firm's operating decisions, including (re)assessments of labor needs, and can shape the amount of employment needed by a firm. Employment decline can lead to all three types of displacement events (plant closures, insufficient work or reduced work hours, or elimination of certain positions).

Supply-side factors, such as taxation, labor availability and cost, and environmental regulation, among others, affect a firm's options on producing goods and services and, therefore, costs associated with production. These factors can shape displacement regardless of demand. However, they are probably more likely to occur in instances of declining demand because changes in the desirability of places or locations for production can trigger a locational shift in production and lead to possible plant closures, as well as other types of displacement events.

2.3 Workers Affected by Displacement

Worker displacement rates capture the number of displaced workers as a proportion of total workers. Displacement rates tend to be cyclical in nature — they rise with recessions and fall when the economy rebounds — and, at the national level, track closely with the unemployment rate. Estimates of the incidence of worker displacement will vary, but one study, which used DWS data spanning several decades (1984-2016), found that three-year rates of worker displacement were as much as two times higher in the aftermath of the Great Recession than in a non-recession period (Farber 2017).

Box 1. Methodological Note: Displacement Rates Vary by Approach and Data Source

Previous research has employed several different approaches to identifying what constitutes the relevant universe of reference workers — i.e., the denominator — for calculating displacement rates. Some studies analyzing the DWS have used a two-year average of long-tenured (those employed by the same employer for at least three years) workers (Gardner 1995; Helwig 2001; 2004). Others have used an "at-risk" group for the universe of reference workers, reflecting "the number of workers… employed at the survey date" (Farber 1997, discussed by Kletzer 1998) and not just those that are long-tenured. Where possible, the universe of reference workers should also be limited to workers ages 20 and older for consistency with the DWS.

In addition, non-DWS data sources tend to estimate lower rates of worker displacement because they are based on workers' experiences over one year and not three years as in the DWS. Compared to the DWS displacement rate estimates of eight to 12 percent for the 1984 to 2016 period (Farber 2017), an older study using data from the Panel Study of Income Dynamics (PSID) estimated that between 1969 and 1986, the annual rate of worker displacement ranged from a low of two percent in 1979 to a high of four percent in 1971 (Stevens 1997). And analysis of data from the earlier waves of the National Longitudinal Survey of Youth (NLS) shows that, for younger workers, annual rates of displacement ranged between two and six percent after controlling for compositional changes in the sample (e.g., higher educational attainment; Kletzer and Fairlie 2003).

Previous research finds that certain groups of workers are more likely to experience displacement events than others. Below we summarize research findings that explore such gaps by gender, race, age, education and industry/occupation:

- Men are generally found to be more likely than women to be displaced from their jobs (Farber 1997; Kletzer and Fairlie 2003); among displaced workers, women are more likely to be displaced due to plant closures whereas men are more likely to be displaced due to slack working conditions (Farber 1997).

- Research on displacement rates by race has been more limited and predominantly focused on differences between Black and white workers, finding that Black workers are more likely than their white counterparts to be displaced (Fairlie and Kletzer 1996; Shiro and Butcher 2022).

- Younger workers tend to have the highest rates of displacement. Displacement rates decline as workers get older, but do begin to increase again toward the end of their careers (Farber 1997; 2017). Differences in displacement rates by age have converged somewhat over the period from 1984 to 2016, with the rates of older workers increasing relative to younger workers (Farber 2017).

- Displacement rates decrease with workers' educational attainment. Workers without a high school diploma are more than twice as likely as those with at least a Bachelor's degree to be displaced from their jobs (Farber 1997; 2017; Shiro and Butcher 2022).

- Displacement is typically less common in white-collar occupations such as managers, professional and technical occupations, and professional services. Sector-wise, workers in manufacturing are far more susceptible to displacement (Farber 1997). The COVID-19 pandemic also contributed to shifts in displacement rates by industry. The leisure and hospitality industry, for example, saw an increase in displacement rates from five percent between 2017 and 2019 to 16 percent between 2019 and 2021 (U.S. Bureau of Labor Statistics 2022).

There are a number of factors that could be driving observed differences in displacement rates. Differences in educational attainment, occupation/industry choice, and level of experience or job tenure exist across many of the groups discussed above, all of which are correlated with the probability of job displacement. Thus, all things equal, displacement rate differences are more likely to reflect differences in worker characteristics correlated with displacement rather than an elevated likelihood of being displaced. As incidence rates of job displacement are not the primary focus of much of the literature reviewed, it is yet to be determined whether differences in worker characteristics are driving observed differences in incidence rates. However, one study did decompose the observed differences in job displacement rates between Black and white workers and found that factors such as occupational sorting are not substantially different in displacement. Employer discrimination in the choice of who to lay off could play a part, though it is uncertain the degree to which this may be the case (Wrigley-Field and Seltzer 2020).

It is also important to note that the nature of job displacement has changed over time, with important implications for which workers are most likely to be impacted by displacement events. Technological advancements, automation, offshoring of shifts in production, greater use of contractors as opposed to attached employees, shifts in consumer demand for different goods and services, greater international competition, as well as prevailing economic conditions have historically meant that worker displacement was largely a blue-collar job phenomenon (Brand 2015). However, more recent corporate downsizing trends have meant that white-collar workers are becoming more prevalent among displaced workers (Kletzer 1998). Indeed, workers in the manufacturing sector as well as craftsworkers, operatives and laborers have historically had some of the highest displacement rates among all workers (about 21 percent between 1981-1983, according to estimates from the DWS); however, by the mid-1990s their rates of displacement had been cut almost in half to 11.8 and 13.5 percent, respectively. Conversely, workers in white-collar industries such as finance, insurance and real estate have seen their rates of displacement increase over time, with about four percent of workers in the industry reporting being displaced in the early 1980s compared with 9.5 percent in the mid-1990s (Farber 1997). These shifts toward more white-collar occupations at risk for job displacement have also led to the convergence in displacement rates for certain groups of workers. For example, the observed gap in displacement rates between Black and white workers has declined substantially in recent years due to the decline in displacement rates in blue-collar occupations, in which Black workers are overrepresented, and the increase in displacement rates in white-collar occupations, in which white workers are overrepresented (Fairlie and Kletzer 1996).

2.4 Outcomes and Effects of Displacement

Re-Employment

Of particular concern to displaced workers is their ability to find alternative employment after the displacement event. Estimates of the share of workers who are re-employed after being displaced have varied substantially, both over time and by data source utilized. For example, historical DWS data from 1984 to 2016, which asks interviewees about their experiences with job displacement over the past three years, show that the share of displaced workers who were employed at the time of the survey ranged from a low of about 50 percent in 2010 to a high of about 75 percent in 1998 (Farber 2017). Researchers generally agree that workers' ability to secure post-displacement employment depends significantly on labor market conditions, with re-employment rates being notably lower during periods of recession.

During these times, employers are reluctant to hire and, because unemployment rates are higher, displaced workers face greater competition for available jobs (Bahn and Cumming 2021; Farber 2017). There is also some evidence that less advantaged groups of workers have greater difficulty in securing employment post-displacement: women, people of color, older and less educated workers are all less likely to be employed post-displacement, even after controlling for a variety of different demographic and work characteristics (Farber 2005; 2017).

Displaced workers typically experience long periods of unemployment, often reaching 12 weeks or more (Fallick 1996; Kletzer 1998; Ruhm 1991; Farber 2017). As with the overall rate of employment post-displacement, the length of time needed to find a new job depends on prevailing economic conditions, with the length of unemployment being significantly longer during periods of recession and the periods immediately following them (Farber 2017; Kletzer 1998). In the years following the Great Recession, the average amount of time workers needed to find a new job peaked at over 20 weeks (Farber 2017). The amount of time needed to secure alternative employment also varies by worker characteristics. Older workers tend to take longer than their younger counterparts to find new jobs, as do those who have been with their employers longer. Women and people of color also tend to take about 1.5 to two weeks longer to find new jobs than their male or white counterparts, respectively. Conversely, more educated workers are able to find employment more quickly, though the difference in timing is not particularly large (less than one week difference; Farber 2017).

While not as well-studied, some researchers have explored the differences between the jobs displaced workers take post-displacement and the jobs they were displaced from. Findings indicate that displaced workers often take on lower-status jobs, have less authority in their new positions, and are less likely to have access to employer-provided benefits (Brand 2006).

Others have explored the relationship between late-career job displacement and retirement decisions, finding that the negative impact of displacement on wages and assets may induce some workers to delay retirement in order to recoup some of those losses. This response has primarily been found among older men, with older women either showing no significant change in decisions around retirement timing (Chan and Stevens 2002).

Wages and Earnings Losses

Analysis of the effects of displacement on worker wages and earnings focuses on three distinct time periods—the period leading up to the displacement event (which can range from a few quarters to a few years), the time period in which the displacement event occurs, and longer-term effects, which are often measured five or more years after the displacement event. Across different years of analysis and different data sources, the overarching findings with respect to the effects of job displacement on workers' wages and earnings have been generally consistent. Earnings commonly follow what has been termed a "dip," "drop" and "recovery" trajectory during the period leading up to, during and after the displacement event (Abbott 2008; Lachowska, Mas, and Woodbury 2019).

The one point on which research is somewhat divided is whether workers' earnings decline significantly prior to displacement. Some have found that workers' earnings will begin to decline in the years leading up to the displacement event (Jacobson, LaLonde, and Sullivan 1993; Stevens 1997), while others have found no material pre-displacement effects on earnings (Schoeni and Dardia 1996). Whether a worker experiences a decline in earnings in the period leading up to displacement depends on the type of displacement event that they experience as well as the characteristics of the worker and their job. Workers who are displaced as part of a mass layoff or plant closure, for example, experience more substantial earnings losses in the period leading up to displacement (Jacobson, LaLonde, and Sullivan 1993; Stevens 1997), likely because such employers are more likely to cut hours and limit wage increases or even reduce wages leading up to the displacement event.

Regardless of whether they experience an initial decline in earnings prior to displacement, workers will experience a dramatic decrease in earnings in the period corresponding to the displacement event (Jacobson, LaLonde, and Sullivan 1993; Stevens 1997; Kletzer and Fairlie 2003; Ruhm 1991). Earnings do recover somewhat in subsequent periods, but research has found that earnings losses are often persistent even after five or more years. Jacobson et al. (1993), for example, find that long-tenure, prime age workers' quarterly earnings were $1,600 below expected (in 1987 dollars) after six years. Similarly, Stevens (1997) finds that wages remain about nine percent below their expected levels six years post-displacement. Others have also found substantial long-term earnings effects (Schoeni and Dardia 1996; Farber 1997; 2017). The ability to find employment post-displacement is a critical factor determining how large and persistent those earnings losses are (Schoeni and Dardia 1996; Stevens 1997). Unfortunately, displaced workers are more likely to be employed part-time post-displacement than non-displaced workers (Farber 2005). For those that are able to find full-time employment post-displacement, earnings losses are quite small in the long-term (Farber 2017).

Different groups of workers have unique displacement experiences and thus distinct effects on their earnings. That is, the type of displacement event and prevailing local economic conditions matter. Those experiencing displacement due to mass layoffs typically experience greater earnings losses overall and are more likely to experience earnings losses in the time leading up to the layoff. Post-displacement earnings and employment outcomes for workers displaced by plant closures are often better than those for laid-off workers. In contrast, other displaced workers are less likely to experience dramatic earnings losses and more likely to recover their losses after five years (Jacobson, LaLonde, and Sullivan 1993). Earnings losses tend to be greater in regions with depressed employment conditions, reflecting a dearth of opportunities for displaced workers (Jacobson, LaLonde, and Sullivan 1993). Losses also depend on whether the worker experiences subsequent job losses after the initial displacement event, with those experiencing multiple job losses experiencing greater wage losses (Stevens 1997; Schoeni and Dardia 1996).

Some researchers have also explored differences in the effects of displacement on workers' earnings by worker demographic characteristics, although it should be noted that variations in the timing of the study, data used, other assumptions made, or sample restrictions imposed make it difficult to compare results across studies and to say definitively whether certain groups are impacted more. Jacobson et al. (1993) found that men's earnings decline more, but women's earnings recovery is slower. In contrast, Farber (2017) finds that women's earnings losses are more negative than men's after controlling for differences in worker characteristics such as age, experience and educational attainment. Some have found that younger workers are also more severely impacted by earnings losses and have greater losses leading up to and corresponding to the displacement event, but they have a greater rate of recovery (Jacobson, LaLonde, and Sullivan 1993; Farber 2017). Others have found that workers with more education tend to have smaller losses, arguing that such workers may have more transferrable (general) human capital whereas less educated workers tend to have more firm-specific human capital (Stevens 1997; Farber 2017).

Displacement doesn't always have a negative effect on workers' earnings. Some workers may actually find jobs that pay more than their pre-displacement positions. Farber (2017) finds that about 39 percent of workers who were displaced from full-time jobs experienced an increase in earnings following displacement. These effects, however, are often masked by the substantial negative earnings effects that many other workers experience.

Health

Researchers also explore several ways in which job displacement can have effects beyond the financial ones described above. Job displacement has been shown to be negatively correlated with indicators of mental and physical health, consistent with the wider body of research documenting the links between socioeconomic status and individual well-being (Brand 2015).

From a mental health perspective, job displacement can affect individuals' perception of their social status and competence as well as the structure and nature of their relationships (Newman 1999), which can be a source of significant stress that can become chronic (Pearlin et al. 1981). The results of these blows to self-perception and increases in stress are increased rates and levels of depressive symptoms, increased anxiety, and reductions in life satisfaction (Brand, Levy, and Gallo 2008; Darity and Goldsmith 1996; Dooley, Prause, and Ham-Rowbottom 2000; Gallo et al. 2000; Leana and Feldman 1992). There has been some concern among researchers in this field that workers with poor mental health may be more likely to be displaced to begin with, presenting a selection problem. However, studies which attempt to correct for selection bias still find a negative relationship between job displacement and mental health (Burgard, Brand, and House 2007).

Job displacement has also been found to negatively affect a number of metrics related to workers' physical health including measures of self-reported health, physical functioning (among older workers), BMI and cholesterol levels, and other effects (Burgard, Brand, and House 2007; Ferrie et al. 1998; Gallo et al. 2000). As with the mental health literature, there is some concern that these findings could be biased as individuals with poor physical health may also be more likely to lose their jobs during a displacement event. The research community remains divided, however, on whether these effects persist after controlling for pre-existing health, lifestyle and demographic characteristics that correlate with poor physical health and job loss (Brand 2015).

Intergenerational Effects

A smaller literature explores the effects that parents' job displacement can have on their children. The rationale for this line of inquiry is that following a job loss, parents have fewer resources in general and may therefore devote fewer resources toward their children's development, affecting the provision of (and attention paid to) educational materials, high-quality child care, etc. (Kalil and Ziol-Guest 2008). Research has found that job displacement among parents can result in increased chances of repeating grades, dropping out of school, and experiencing punitive measures such as suspension or expulsion (Johnson, Kalil, and Dunifon 2012; Kalil and Ziol-Guest 2008; Stevens and Schaller 2011), which can have adverse effects on these children long after they reach adulthood in the form of lower incomes (Page, Stevens, and Lindo 2007).

Another body of literature has examined the intergenerational factors that impact the likelihood of displacement and labor market outcomes post-displacement. Recent research suggests that adult workers with lower-income parents are at greater risk of displacement than those with higher-income parents (Shiro and Butcher 2022), and these workers face worse labor market outcomes (e.g., increased earnings losses, higher unemployment rates) after a displacement event (Kaila, Nix, and Riukula 2022).

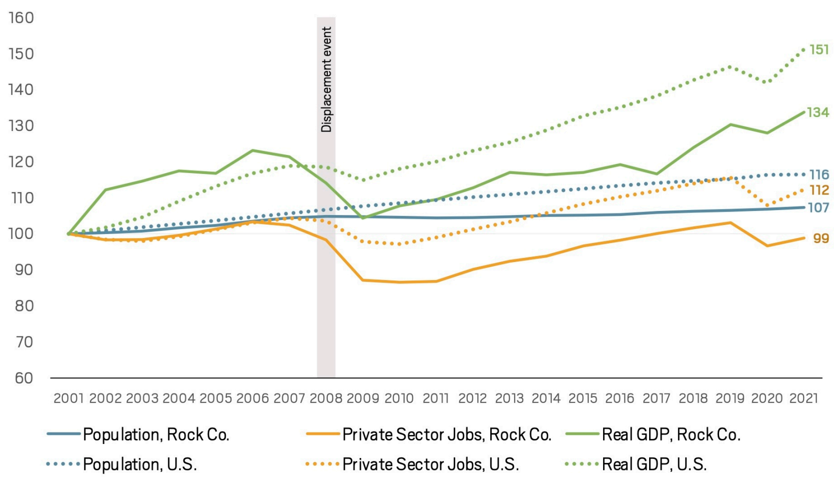
Effects on Local Economies

A separate yet related stream of research has examined the impacts of Type 1 (plant or facility closing or moving) or Type 3 displacement (eliminated positions) event on surrounding economies, particularly the broader impacts on the local tax base and jobs at suppliers and related firms. For example, the closure of two coal power plants in Adams County, Ohio was estimated to reduce local tax revenues by $8.5 million, and county general fund revenues were estimated to decline by more than 30% (Jolley et al. 2019). The Lordstown, Ohio General Motors (GM) plant, which first opened in 1966, was the site of three displacement events from 2017 to 2019, when it ultimately closed. Over these three years, the plant eliminated more than 4,300 jobs. In addition to these direct jobs losses, there was a ripple effect throughout the region. At least three local suppliers for the plant shuttered, together eliminating more than 300 jobs (Lendel et al. 2019).

Box 2. Case Study: Janesville, Wisconsin

Janesville, Wisconsin, located in Rock County, was home to the oldest GM assembly plant, dating back to 1919. During its prime, the plant employed approximately 7,000 workers. In 2008 — coinciding with the onset of the Great Recession — the GM plant halted their SUV assembly; in addition to eliminating about 2,000 GM workers, it also led to the loss of about 1,200 jobs at suppliers. The plant ultimately closed in 2009 (Gardner 2015; Leute 2009). Local gross domestic product (GDP) and jobs showed sharp declines in the years before and after 2008, even though they tracked (or out-performed) the U.S. up until this point. Despite subsequent upticks in jobs and GDP, which are signs of possible economic recovery, growth trajectories remain well below the U.S.

Population, Jobs, and Gross Domestic Product (GDP) Growth Trends, 2001-2021 (2001=100)



	Change, 2008-2021	
	Rock Co.	**U.S.**
Population	2.3%	9.1%
Private Sector Jobs	0.5%	8.4%
Real GDP (Private Industries)	17.2%	27.5%

Note: This chart shows population, jobs, and GDP growth rates relative to their respective 2001 levels (recorded as 100). In 2021, Rock County's GDP was 34% above 2001 levels (vs. 51% in the U.S.); population was 7% above 2001 levels (vs. 16% in the U.S.); and private sector jobs were 1% below 2001 levels (vs. 12% above 2001 levels in the U.S.). GDP growth controls for inflation.

Source: U.S. Census Bureau Population Estimates Program (PEP), Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW), Bureau of Economic Analysis Gross Domestic Product by County, Metro, and Other Areas; Mass Economics analysis.

In 2017, journalist Amy Goldstein published Janesville: An American Story, documenting the aftermath of the plant's closure. In addition to capturing effects on the local economy, Goldstein follows several former GM workers and their jobs trajectories. Some remained employed with GM and took transfers to other midwestern GM locations, such as Fort Wayne or Kansas City (colloquially known as "Janesville West"), while others sought out retraining to embark on entirely new career paths. Goldstein surveyed thousands of local workers on their employment outcomes and analyzed multiple state and local datasets. Consistent with other research, the oldest displaced workers tended to experience the biggest drop in earnings (in both absolute and relative terms), among workers that got retrained.

2.5 Major Data Sources Used to Study Displacement

Past research has leveraged numerous data sources to analyze worker displacement. While the DWS is the most commonly used data source, researchers have found relative advantages, as well as some disadvantages, to other data, depending on their research questions. Table 1 provides an overview of the data sources used by worker displacement studies, and the remainder of this section discusses the major data sources in more detail.

Table 1. Overview of Data Sources Used by Worker Displacement Studies

Data Source on Displacement	Provider	First Year of Data	Frequency	Geographic Level	Relevant Studies	Average Age of Relevant Studies
Displaced Worker Supplement (DWS)	Census Bureau	1984	Biennially	National (limited coverage of states, metro/nonmetro by state, some metros)	Addison and Portugal 1989; Bana 2018; Farber 1997; 2003; 2005; 2015; 2017; Fairlie and Kletzer 1996; Gardner 1995; Gibbons and Katz 1991; Hamrick 2001; Helwig 2001; 2004; Howland 1988; Jackson 2021; Schmitt 2004; Song 2018; Wrigley-Field and Seltzer 2020	18 years
Panel Study of Income Dynamics (PSID)	University of Michigan	1968	Biennially	National	Page, Stevens, and Lindo 2007; Ruhm 1991; Shiro and Butcher 2022; Stevens 1997	19 years
National Longitudinal Surveys (NLS)	Bureau of Labor Statistics	1966 (1979 for active cohorts)	Biennially	National	Dooley, Prause, and Ham-Rowbottom 2000; Gustafson 1998; Kletzer and Fairlie 2003	23 years
State Administrative Data (forms the backbone of BLS QCEW data)	State Departments of Employment Securities (that administer unemployment benefits)	Varies	Quarterly	Varies (town, county, etc.)	Jacobson, LaLonde, and Sullivan 1993; Lachowska, Mas, and Woodbury 2019; Lengermann and Vilhuber 2002; Schoeni and Dardia 1996	21 years
Establishment-Level Data	Various but includes Dun & Bradstreet, YTS	Varies; YTS has jobs data back to 1997	Annually	Point	Howland 1988	35 years

Note: Kaila et al. 2022, Oreopoulous et al. 2008, Raposo et al. 2021, and Schmieder et al. 2022 use Finnish, Canadian, Portuguese, and German administrative data, respectively.

Current Population Survey - Displaced Worker Supplement

The Displaced Worker Supplement (DWS) is a national supplement to the Current Population Survey (CPS) and was first published in 1984. While the CPS is conducted every month, the DWS is conducted every two years and asks surveyed individuals about their job displacement history over the last three calendar years (i.e., the January 2022 survey asks about the period from January 2019 to December 2021). DWS only captures workers who are civilians and are at least 20 years old, and analysis of DWS generally emphasizes long-tenured workers (i.e., those who have been employed by their previous employer for at least three years) (Herzenberg, Price, and Wial 2005). DWS tracks displacement resulting from plant closures or moves (Type 1), insufficient work (Type 2), or the elimination of a position or shift (Type 3) ("Current Population Survey, January 2022: Displaced Worker, Employee Tenure, and Occupational Mobility Supplement File" 2022).

Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID) is a biennial national survey of individuals and households that dates back to 1968. PSID is purported to be the "world's longest running, nationally representative household panel survey," capturing the experiences of 82,000 people across seven generations ("PSID 2019 Release - Data Highlights" 2019). Unlike DWS, PSID does not cover all three types of displacement events; generally, studies using PSID focus at minimum on Type 1 displacement (plant closures or moves), as in Page, Stevens, and Lindo (2009) and Shiro and Butcher (2022).

Others have loosened the definition of a displacement event to include layoffs and firings (Stevens 1997; Ruhm 1991), but since these two events cannot be disentangled, they are not necessarily consistent with displacement as defined by DWS. However, previous research has found that PSID data reasonably track DWS data when it comes to predicting unemployment after a displacement event (Ruhm 1991).

National Longitudinal Surveys

The National Longitudinal Surveys (NLS) track employment conditions for several cohorts, and data for the active cohorts — the oldest of which was first interviewed in 1979 — are available on a biennial basis ("National Longitudinal Surveys," n.d.). Since the survey is designed to follow different groups of youth throughout their lives, NLS data are best suited for analyzing the experiences of displaced younger workers. Similar to PSID, NLS does not cover all three types of displacement events; it mainly covers Type 1 or Type 3 events through plant closures or layoffs (Gustafson 1998; Kletzer and Fairlie 2003). Importantly, NLS is able to differentiate layoffs from firings, unlike PSID (Kletzer and Fairlie 2003).

State Administrative Data

State administrative data derived from state unemployment insurance records offer detailed employment and wage information by industry, often at multiple geographic levels. These data are eventually remitted to the Bureau of Labor Statistics (BLS) to serve as the backbone of the Quarterly Census of Employment and Wages (QCEW) program, and previous research has used (often confidential) versions of these data for state-level studies to link employees to employers and track earnings before, during, and after displacement events, such as in Jacobson, LaLonde, and Sullivan (1993). The types of displacement events tracked tend to vary by state (and thus, data source). Using data from the state of Pennsylvania, Jacobson, LaLonde, and Sullivan (1993) identify a mix of Type 1 and 3 events by creating a "mass layoff" group of workers that could have resulted from plant closures or layoffs. Using data from the state of Washington, Lachowska, Mas, and Woodbury (2019) can identify Type 2 events through reduced work hours. It is worth noting that administrative data may not differentiate between layoffs and voluntary separations (Lendermann and Vilhuber 2002).

Establishment-Level Data

Establishment-level data provide employment data on specific businesses, and the establishments are generally tagged with their detailed industry and geocoded (i.e., "point") location. Some datasets (e.g., Your-economy Time Series, or YTS) may also provide detailed information on business moves and closures over their lifetime, meaning they capture certain displacement events directly. These data provide a clear picture of Type 1 displacement (plant closures) and could provide insights on Type 3 displacement (position or shift eliminated) if criteria for mass layoffs are developed.

Though previous research has pointed out the value of using establishment-level data to understand better the job dynamics associated with worker displacement,[7] these data have not been widely used in the study of worker displacement. Only one paper has been identified that has used establishment- or firm-level data to analyze worker displacement (Howland 1988).

7. For example, Kletzer et al. 1998 has pointed out the value of "plant-level data with information on turnovers (quits, layoffs, firings, recalls, hirings)."

Comparing the Major Data Sources

There are benefits and drawbacks associated with each of these datasets. Table 2 summarizes some of their tradeoffs, including the type of data (administrative vs. survey vs. third-party), necessary for understanding the quality and representativeness of the underlying data; whether the three types of displacement are covered ("displacement coverage"); available geographies; worker demographic detail; whether the data source is suitable for longitudinal analysis to track worker outcomes before, during and after displacement events ("longitudinal"); whether the data source supports intergenerational analyses to track worker outcomes and effects on earlier or subsequent generations ("intergenerational"); and whether the data source allows for the creation of a non-displaced benchmark ("non- displaced").

Table 2. Tradeoffs of Major Displacement Data Sources

	DWS	PSID	NLS	State Administrative Data	Establishment-Level
Type	Survey	Survey	Survey	Administrative	Third-Party
Displacement Coverage	Types 1, 2, 3	Types 1, 3*	Types 1, 3	Types 1, 2, 3**	Types 1, 3
Available Geographies	U.S., states, some metros	U.S.	U.S.	States, metros, counties, towns	Point
Worker Demographic Detail	Yes	Yes	Yes	No	No
Longitudinal	No	Yes	Yes	Yes	No
Intergenerational	No	Yes	Yes***	No	No
Non-Displaced	No	Yes	Yes	Yes	Yes

* PSID is unable to differentiate layoffs from firings.

** This varies by underlying data source, but it's worth noting that methods have been developed to estimate different types of displacement, such as creating a "mass layoff" group of workers (Jacobson, LaLonde, and Sullivan 1993).

*** The NLSY79 Child and Young Adult cohort is comprised of the children of the women in the NLSY79 cohort.

All of the major data sources are publicly available except for the establishment-level data, which come from third-party, private sources. Public data are generally high-quality, and among public data sources, administrative data are the highest quality and generally considered the most reliable. This is because they are often derived from data that are required by law to be collected (e.g., unemployment insurance records). Survey data are a notch below administrative data when it comes to quality and reliability. It is not uncommon for survey data to be plagued by problems such as retrospective or recall bias, in which enough time has passed between the event in question and the date of the interview that the interviewee's recollection of the event is impaired. Retrospective bias has long been identified as an issue for DWS (Evans and Leighton 1995; Herzenberg, Price, and Wial 2005), and results should be interpreted accordingly. Data from third-party, private sources often fills a gap or need left by publicly available data, such as geographic specificity, but depending on the source in question, this may come at the expense of quality.

Other Data Sources

In addition to the main data sources identified in the previous section, other data sources identified in the literature include the Health and Retirement Study to analyze the health outcomes of displaced workers (Gallo et al. 2000; Brand, Levy, and Gallo 2008; Chan and Stevens 2002); the Survey of Income and Program Participation (Stevens and Schaller 2011; Kalil and Ziol-Guest 2008); the American Changing Lives Study (Burgard, Brand, and House 2007); the Wisconsin Longitudinal Study (Burgard, Brand, and House 2007); and the Women's Employment Study in Michigan (Johnson, Kalil, and Dunifon 2012).

3. REPLICATING THE PREVIOUS STUDY'S APPROACH

3.1 Overview

This section replicates the approach used by Herzenberg, Price, and Wial (2005). Following the previous study, the approach identifies "partial geographies," those that are partly within and partly outside of the Appalachian Region, and crosswalks them to the Public Use Microdata Areas (PUMAs).[8] The foundation of the previous approach relies on key datasets that are only available down to the PUMA geography. These data are utilized in logit models which predict the probability that a PUMA is located in the region, thus providing a predicted "Appalachian share" for each partial geography. This task also calculates a simple share of the labor force in Appalachia for each partial geography for comparison.

3.2 Data Sources

There are three primary data sources used in this analysis. From the Current Population Survey (CPS), we use both the Displaced Worker Supplement and basic monthly microdata for January of the survey years (2014, 2016, 2018, 2020, and 2022). We also use the U.S. Census Bureau American Community Survey (ACS) microdata from 2016, which are available at the PUMA geography.[9]

3.3 Approach

Identifying Partial Geographies

Partial geographies are those that are partly within and partly outside of the Appalachian Region. The partial geographies consist of metropolitan areas, as well as nonmetropolitan portions of states. The 2014 survey data are reported in the June 2003 Metropolitan Statistical Area (MSA) definition, and the 2016, 2018, 2020, and 2022 survey data are reported in the February 2013 MSA definition. Using the November 2021 county definition of the Appalachian Region and the respective MSA vintage definitions (June 2003 for the 2014 survey and February 2013 MSA definition for the 2016, 2018, 2020, and 2022 surveys), up to 60 partial geographies exist, but not all are necessarily present in the CPS or DWS data. For example, because 100% of West Virginia is included in the Appalachian Region,

8. See https://www.arc.gov/appalachian-counties-served-by-arc/ for a map and list of the counties within the Appalachian Region. In this case, "crosswalk" refers to the process of converting data in one geographic structure to another.

9. We decided to use 2016 data after assessing model fit on other years of microdata and determining that 2016 had the best performance. 2016 has the added benefit of being the midpoint of the study period (2011-2021).

there is no nonmetro West Virginia partial. Similarly, because 100% of nonmetro Pennsylvania is in the Appalachian Region in the 2013 MSA definition, there is no nonmetro Pennsylvania partial in the 2016, 2018, 2020, and 2022 surveys. (See Table 3 and Table 4 for lists of the partial geographies.)

Table 3. List of MSA Partial Geographies

	2003 MSA Definition	2013 MSA Definition
MSAs	Albany, NY	Albany, NY
	Allentown, PA	Allentown, PA
	Athens, GA	Athens, GA
	Atlanta, GA	Atlanta, GA
	Bowling Green, KY	Bowling Green, KY
	Canton, OH	Canton, OH
	Cincinnati, OH	Cincinnati, OH
	Greenville, SC	Columbus, OH
	Harrisburg, PA	Greenville, SC
	Lexington, KY	Harrisburg, PA
	Memphis, TN	Lexington, KY
	Montgomery, AL	Memphis, TN
	Nashville, TN	Montgomery, AL
	New York, NY	Nashville, TN
	Roanoke, VA	New York, NY
	Tuscaloosa, AL	Roanoke, VA
	Washington, DC	Washington, DC
	Winchester, VA	Winchester, VA
		Winston-Salem, NC

Table 4. List of Nonmetro Partial Geographies

	2003 MSA Definition	2013 MSA Definition
Nonmetro Portions of States	Alabama	Alabama
	Georgia	Georgia
	Kentucky	Kentucky
	Maryland	Maryland
	Mississippi	Mississippi
	New York	New York
	North Carolina	North Carolina
	Ohio	Ohio
	Pennsylvania	South Carolina
	South Carolina	Tennessee
	Tennessee	Virginia
	Virginia	

Creating a Crosswalk Between the PUMAs and Partials

In order to determine the Appalachian Region share of the partial geographies, the logit models are specified using variables that appear in both the CPS and DWS data, as well as ACS microdata. The ACS microdata are reported at the PUMA geography, so it is necessary to create a geographic crosswalk between the partial geographies and the PUMAs. Any PUMA that contains or is contained within an Appalachian county is considered part of the Appalachian Region, though it is worth noting that the geographic accuracy of the PUMA approximation varies widely by partial geography.

Assessing Variables of Interest

At the outset, one of the goals of this analysis was to incorporate more socioeconomic and work-related (e.g., industry and occupation) variables when estimating Appalachian Region displacement rates. In terms of socioeconomic variables, the project team considered age, citizenship status, certain health condition and disability status variables (e.g., personal care difficulties, blindness or vision problems, deaf or hearing problems, difficulty performing tasks outside of the home, physical limitations or difficulties, cognitive difficulties), educational attainment, ethnicity, marital status, race, sex, veteran status, and year of immigration if applicable. In terms of work-related variables, the project team considered class of worker, employment status, industry, labor force status, and occupation.

Since the data were reported in two sets of Census industry vintages (the 2003 and 2013 MSA definitions), the project team rolled up industry and occupation to sector-equivalent levels to approximate the same universe of industries and occupations across survey years.[10]

Specifying Logit Models

The project team tested a series of logit models relying on combinations of socioeconomic and work-related variables. The models were specified using all the PUMAs in the partial geographies. The best model[11] took the form of:

$$\begin{aligned} ARC = f(&Age + Citizen + DiffCare + DiffHear + DiffMob + DiffPhys + DiffRem \\ &+ Education + Hispanic + Sex * Marital\ Status + Race + Veteran\ Status \\ &+ Year\ of\ Immigration + Class\ of\ Worker + Labor\ Force + Industry \\ &* Employment\ Status + Occupation * Employment\ Status) \end{aligned}$$

10. There are incongruities in the CPS-reported military industries compared to the Census-reported military industries. This task generally follows the CPS-reported military industries.

11. The best model is determined by having the lowest Akaike Information Criterion (AIC); see Table 33 in section 9.4 for additional details.

Due to limited numbers of observations when implemented in the partial geographies, we removed the industry and occupation and employment status interaction terms, as well as the physical limitations or difficulties and cognitive difficulties terms.

After determining the final specifications for the model, the model was run separately for each partial geography in order to calculate partial-specific coefficients. These coefficients were then applied to observations in the corresponding partial geography to calculate the Appalachian Region share of the partial geography.

Calculating Simple Labor Force Share

From the PUMA-partial crosswalk, it is possible to determine the share of population in each partial geography that is in the Appalachian Region. We applied this share to the ACS labor force to estimate the share of labor force in each PUMA- partial geography in the Appalachian Region.

Applying the Logistic and Labor Force Weights to DWS and CPS

From the logit models, the logistic weight share w_{lg} for partial geography α is:

$$w_{lg,\alpha} = p_\alpha = \frac{\left(\frac{p_\alpha}{1-p_\alpha}\right)}{1+\left(\frac{p_\alpha}{1-p_\alpha}\right)} = \frac{e^{\beta_{0,\alpha}+\beta_{i,\alpha}x_\alpha}}{1+e^{\beta_{0,\alpha}+\beta_{i,\alpha}x_\alpha}}$$

The labor force weight share w_{lf} for partial geography α across PUMAs 1 to N is:

$$w_{lf,\alpha} = \frac{\sum_{i=1}^{N} LaborForce_i * \frac{TotPop_{i,ARC}}{TotPop_i}}{\sum_{i=1}^{N} LaborForce_i}$$

These weights were joined to partial geography observations in the DWS and CPS data. The Appalachian Region portion corresponded to the given weights (DWSUPPWT in DWS and WTFINL in CPS) multiplied by these Appalachian Region weight shares, and the non-Appalachian Region shares corresponded to the given weights multiplied by (1-Appalachian Region weight share).

3.4 Analysis of DWS

In addition to the exploration and evaluation of alternate methods of analyzing displacement, there were several important takeaways from analyzing displacement using the previous study's approach.

Displacement Trends Over Time

Nationally and in the Appalachian Region, displacement rates have been trending downward. The number of displaced workers nationally peaked during the Great Recession (2007-2009). The period leading up to the COVID pandemic (2017-2019) marked the lowest levels of displacement at any point since 1993. COVID-related displacement (from 2019-2021) was estimated to be only half of peak levels of the Great Recession. In the rest of the U.S., the 1993-2003 period reported an overall displacement rate of 3.2% compared to 2.3% from 2011-2021. In the Appalachian Region, the 1993-2003 period reported an overall displacement rate of 3.3% compared to 2.3% from 2011-2021. While the displacement rates in the Appalachian Region and rest of U.S. over the full 2011-2021 time period were the same — both 2.3% — the Appalachian Region has had lower displacement rates compared to the rest of the U.S. more recently (i.e., in the 2017-2019 and 2019-2021 time periods).[12] (See Table 5.)

Table 5. Displacement in Appalachian Region and Rest of U.S. Using Previous Study's Approach

	APPALACHIAN REGION			REST OF U.S.			% POINT DELTA
Year	Total Jobs*	Estimated Number of Displaced Workers	Estimated Displacement Rate	Total Jobs*	Estimated Number of Displaced Workers	Estimated Displacement Rate	Appalachian Region – Rest of U.S.
2011-2013	12,017,300	378,700	3.2%	129,137,000	3,913,200	3.0%	0.1%
2013-2015	12,260,100	266,100	2.2%	133,891,600	2,925,300	2.2%	0.0%
2015-2017	12,768,100	302,600	2.4%	136,566,300	2,678,800	2.0%	0.4%
2017-2019	12,987,800	202,600	1.6%	140,304,100	2,469,500	1.8%	-0.2%
2019-2021	13,061,900	280,100	2.1%	138,791,100	3,316,200	2.4%	-0.2%
2011-2021	-	-	2.3%	-	-	2.3%	0.0%

Note: The 2011-2021 displacement rate reflects a weighted average of the five individual surveys.
Because of rounding, deltas may not match those calculated from table values.
*Includes displaced, not currently employed. Source: CPS DWS; dF-QWI; Mass Economics analysis.

12. It is worth noting the reported rates in this paragraph (and throughout the entire report) utilize an updated, improved, and consistent methodology that reflects a weighted average of the DWS survey periods in order to produce a more accurate result for the aggregate period. I.e., these historic numbers will differ from the published Wial et.al. report covering the 1993-2003 period.

Characteristics of the Displaced in Appalachia

From 2019 to 2021, the most recent period for which displacement data are available, we estimate that approximately 280,100 workers were displaced in Appalachia, reflecting a displacement rate of about 2.1%. In terms of affected groups, displacement rates are higher for older workers. Workers with higher levels of education tend to report lower displacement rates (e.g., workers with at least a bachelor's degree report displacement rates that were more than a percentage point lower than those with only a HS diploma in 2013-2015 and 2015-2017). In recent years (2019- 2021), workers of color have reported displacement rates that are less than half of those of White, non-Hispanic workers. Workers in service-oriented industries report lower displacement rates than those in goods-producing industries. From 2011-2013 to 2019-2021, there was a relatively large decline in the displacement rate for the entire Appalachian Region. The absolute change in displacement rate in the Appalachian Region was -1.1% (versus -0.6% for the rest of the U.S.) On a percent basis, displacement in the Appalachian Region declined by 32% versus 21% in the rest of the U.S. Within the Appalachian Region, the decline in displacement rate was statistically significant for all workers; males; workers ages 35-54; those with only a HS diploma; white, non-Hispanic workers; workers displaced from goods-producing industries; and workers in metro areas. There has also been a statistically significant decline in the share of displaced workers who are unemployed at the time of the survey.

Displacement Experience in Appalachia

Over the past decade, 42% of displacements in the Appalachian Region have resulted from Type 1 events (plant closures) versus 37% in the rest of the U.S. It is far more likely for displaced workers to have worked at the job from which they were displaced for 3 to 10 years, rather than 10+ years. The vast majority were full-time at the job from which they were displaced. Most displaced workers are currently employed, and generally, more than 45% spend less than a month and a half without work after their displacement. Displaced workers in Appalachia are more likely to not be in the labor force than those in the rest of the U.S. (22% versus 19%). Despite legislation like the Worker Adjustment and Retraining Notification (WARN) Act, most displaced workers received no advance notice. Most displaced workers currently have health insurance. Finally, most have not moved from their place of residence (city or county) after their job loss.

Among displaced workers who were displaced from full-time jobs, over 60% became re-employed, and it is far more likely that they are re-employed in full-time, rather than part-time, jobs. In every time period, over half of displaced full- time workers are earning less than they were at their previous job, ranging from 53% to 64% in Appalachia, and from 62% to 70% in the rest of U.S.

Displacement by Geography

While the overall displacement rate in the Appalachian Region over the 2011-2021 period was 2.3%, the state rates varied from a low of 1.6% in the Appalachian portions of Mississippi and New York to a high of 2.8% in the Appalachian portion of Ohio. The Appalachian portion of Maryland had a rate of 5.3% but the absolute numbers and underlying sample size is notably lower compared to the other states and should be interpreted with caution. (See Table 6.)

Table 6. Displacement Rates by Appalachian Region Portion of States, 2011-2021

	Displacement Rate
Non-Appalachian Region U.S.	2.3%
Appalachian Region	2.3%
Alabama	1.7%
Georgia	2.2%
Kentucky	2.3%
Maryland	5.3%
Mississippi	1.6%
New York	1.6%
North Carolina	2.1%
Ohio	2.8%
Pennsylvania	2.6%
South Carolina	1.7%
Tennessee	2.5%
Virginia	2.4%
West Virginia	2.7%

Source: CPS DWS; Mass Economics analysis.

There are no statistically significant differences in displacement rates for metro vs. nonmetro parts of the Appalachian Region. While not statistically significant, it is worth noting that the displacement rates for male workers, workers ages 35-54, workers without a high school diploma, and workers in goods-producing industries were lower in the metro parts of the Appalachian Region compared to the nonmetro parts. (See Table 7.)

Table 7. Displacement Rates by Appalachian Region Metro/Nonmetro, 2011-2021

	APPALACHIAN REGION			
	Total	**Metro**	**Nonmetro**	**Metro-Nonmetro, % Point Delta**
All	2.3%	2.2%	2.3%	-0.1%
Gender				
Female	2.1%	2.1%	2.0%	0.1%
Male	2.4%	2.4%	2.6%	-0.2%
Age				
20-34	1.4%	1.4%	1.3%	0.1%
35-54	2.4%	2.3%	2.6%	-0.4%
55+	3.1%	3.3%	2.8%	0.4%
Education				
Less than High School	2.6%	2.2%	3.2%	-1.0%
High School	2.4%	2.4%	2.5%	0.0%
Some College or Associate's Degree	2.4%	2.6%	2.1%	0.4%
Bachelor's Degree or Higher	1.9%	1.9%	2.0%	-0.1%
Race				
White, non-Hispanic	2.4%	2.4%	2.4%	0.0%
People of Color	1.9%	1.9%	1.8%	0.1%
Industry (excl. public admin, gov)				
Goods-Producing	3.0%	2.7%	3.3%	-0.6%
Services	2.1%	2.2%	2.0%	0.2%

Note: Because of rounding, deltas may not match those calculated from table values.
Source: CPS DWS; Mass Economics analysis.

Displacement by Industry

As discussed above, displacement rates can vary over time, place, and by worker demographics. However, they can vary most dramatically across industry. The 2019-2021 time period had the largest range in displacement rates across the top ten Census industries, varying from 55% in Knitting Fabric Mills and Apparel Knitting Mills to 12% in Shoe Stores. (See Table 8.)

Table 8. Industries with High Displacement Rates Nationally, 2019-2021

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Number of Displaced Workers, U.S.
1	Knitting Fabric Mills, and Apparel Knitting Mills	55%	4,700
2	Railroad Rolling Stock Manufacturing	34%	6,700
3	Oil and Gas Extraction	22%	15,900
4	Other Consumer Goods Rental	20%	15,300
5	Engine, Turbine, and Power Transmission Equipment Manufacturing	19%	7,300
6	Clay Building Material and Refractories Manufacturing	16%	2,800
7	Miscellaneous Nonmetallic Mineral Product Manufacturing	13%	5,200
8	Scenic and Sightseeing Transportation	13%	3,500
9	Petroleum Refining	12%	27,800
10	Shoe Stores	12%	9,100

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

The industries with the highest levels of displacement also changed dramatically over time. Out of 23 unique Census industries in the top five in the 2011-2013, 2013-2015, 2015-2017, 2017-2019, or 2019-2021 time periods, only two Census industries made the top five in multiple time periods: Coal Mining and Other Information Services (shaded in green in Table 9). In other words, the top five industries were completely different from the top five in the previous time period except for 2015-2017 (Coal Mining) and 2017-2019 (Other Information services). (See Table 40 through Table 51 in section 9.6 in the appendix for the top ten Census industries in each time period.)

Table 9. Census Industries with Top Five Displacement Rates Nationally, 2011-2021

Census Industry	2011-2013	2013-2015	2015-2017	2017-2019	2019-2021
Farm Supplies Merchant Wholesalers	20%				
Water Transportation	17%				
Coal Mining	17%		25%		
Office Supplies and Stationery Stores	16%				
Ship and Boat Building	15%				
Clay Building Material and Refractories Manufacturing		30%			
Miscellaneous Petroleum and Coal Products		23%			
Leather + Hide Tanning + Finishing, + Other Leather + Allied Product Mfg.		23%			
Other Information Services, E.G. Libraries, Archives, and Internet Publishing, Broadcasting, and Web Search Portals		20%		20%	
Aerospace Products and Parts Manufacturing		16%			
Sewing, Needlework, and Piece Goods Stores			23%		
Metals and Minerals, Except Petroleum, Merchant Wholesalers			19%		
Scenic and Sightseeing Transportation			19%		
Construction, and Mining and Oil and Gas Field Machinery Manufacturing			17%		
Coating, Engraving, Heat Treating, and Allied Activities				23%	
Book Stores and News Dealers				22%	
Software Publishers				15%	
Other Direct Selling Establishments				13%	
Knitting Fabric Mills, and Apparel Knitting Mills					55%
Railroad Rolling Stock Manufacturing					34%
Oil and Gas Extraction					22%
Other Consumer Goods Rental					20%
Engine, Turbine, and Power Transmission Equipment Manufacturing					19%

Source: CPS DWS; Mass Economics analysis.

Driven by the consistently large size of some industries nationally, there is less variation in the industries driving displacement in absolute terms. There are only 18 unique Census industries that appear in the top ten in one of the five time periods, compared to 38 industries when measured on a displacement rate basis. Seven of the top ten in the 2011- 2013 time period were also in the top ten in the latest 2019-2021 time period. (See Table 10 and Table 52 through Table 56 in the appendix.)

Table 10. Census Industries with the Most Displaced Workers Nationally, 2011-2021

Census Industry	NUMBER OF DISPLACED WORKERS (THOUSANDS) U.S. 2011-2013	2013-2015	2015-2017	2017-2019	2019-2021	RANKS 2011-2013	2013-2015	2015-2017	2017-2019	2019-2021
Construction	410	217	165	193	213	1	1	1	1	2
Restaurants and Other Food Services	200	142	147	88	352	2	2	2	3	1
General Medical and Surgical Hospitals and Specialty (E.G. Psychiatric and Substance Abuse) Hospitals	127	86	66	53	74	3	5	8	6	6
Elementary and Secondary Schools	124	99	60	58	88	4	3	9	5	4
Computer Systems Design and Related Svcs.	101	97	109	118	85	5	4	3	2	5
Insurance Carriers	91	52	80			6	10	5		
Architectural, Engineering, and Related Svcs.	81		94	40		7		4	10	
Supermarkets and Other Grocery (Except Convenience) Stores	72	54				8	9			
Banking and Related Activities	68	83		44	68	9	6		8	9
Colleges, Junior Colleges, Universities, and Professional Schools	67		79	53	61	10		6	7	10
Lessors Of Real Estate and Offices Of Real Estate Agents and Brokers		72					7			
Support Activities For Mining		56	77				8	7		
Department Stores			48					10		
Agencies, Brokerages, and Other Insurance Related Activities				71					4	
Nondepository Credit and Related Activities				44					9	
Other Amusement, Gambling, and Recreation					112					3
Mgmt., Scientific, and Technical Consulting					70					7
Outpatient Care Centers					69					8

Source: CPS DWS; Mass Economics analysis.

4. DEVELOPING AN INDUSTRY-BASED APPROACH FOR UNDERSTANDING DISPLACEMENT

4.1 Overview

This analysis tests two other methods for estimating displacement in the Appalachian Region. The first method is an alternate approach to the treatment of partial geographies, in which we use county-level separation and hire ratios to split DWS observations into Appalachian Region and non-Appalachian Region portions. The second method uses national-level Census industry displacement rates applied to detailed 6-digit NAICS (North American Industry Classification System) county-level data. By aggregating county-level data, we are able to create Appalachian Region and non-Appalachian Region geographies. Using both methods helps to clarify whether local industry mix is driving differential displacement rates and the extent to which other location- and geography-specific factors are playing a role.

4.2 Data Sources

Several sources of public and private data are leveraged in this analysis. From the Bureau of Labor Statistics and data-Fab, we use private-sector, county-level Quarterly Census of Employment and Wages (QCEW) 6-digit NAICS data. These data are used to obtain county- and industry-specific employment to which industry-specific displacement rates are applied. From the Census Bureau, we use the CPS DWS, as well as county-level Quarterly Workforce Indicators (QWI) data at the 4-digit NAICS. The CPS DWS data are used to provide a national profile of displacement by industry. QWI data are used to provide information on separations and hires at the county level within the partial Appalachian Region geographies. From the University of Wisconsin Business Dynamics Research Consortium, we use the Your- economy Time Series (YTS) establishment microdata for 6-digit NAICS. The YTS data are used to provide county-level, industry-specific estimates of Type 1 displacement (moves and closures). All NAICS data are standardized to the 2017 classification system.

4.3 Industry Detail and Crosswalks

It was necessary to create a crosswalk between the Census industries and the NAICS industries. The DWS data are reported in Census industries, while most other economic industry data use NAICS codes. DWS data for the 2014, 2016, and 2018 surveys are reported in 2012 Census industries, while DWS data for the 2020 and 2022 surveys are reported in 2017 Census industries.

To ultimately arrive at a dataset featuring 2017 NAICS codes, first we had to crosswalk 2012 Census industries to 2017 Census industries, a process that relied on Census documentation and data-Fab crosswalks. We then had to crosswalk 2017 Census industries to 2017 NAICS industries, for longitudinal consistency and alignment between data sources. Across the five survey periods (2014, 2016, 2018, 2020, 2022), most of the displaced worker observations are available at the equivalent of at least a 4-digit NAICS level.

It is also worth noting that the universe of industry coverage in CPS (and thus DWS) data differs from QCEW. At least part of this difference can be attributed to the fact that complete QCEW data with 6D NAICS industry detail are only available for the private sector, whereas CPS data covers public and private sector jobs. While the largest share of jobs in both data sources is in the Health Care and Social Assistance sectors, there are several sectors for which the share of jobs in CPS far exceeds QCEW: Private Only. (See Table 11.) The largest difference is Educational Services, which have 10% of jobs in CPS (including public jobs) but only 2.3% of jobs in QCEW: Private Only (a difference of 7.7%). However, the values are much closer for QCEW: Private + Public, at 9.3%. Across the industry sectors, the largest difference in share for QCEW: Private + Public compared to CPS is only 3.3% (Accommodation + Food Services).

Table 11. Comparing DWS industry coverage to QCEW

Industry Sector	SHARE OF U.S. EMPLOYMENT, 2011-2021				% POINT DELTA
	QCEW Jobs: Private Only	QCEW Jobs: Private + Public	CPS Jobs	Jobs in Industries From Which Workers are Displaced in DWS	CPS Jobs –QCEW Jobs: Private + Public
Healthcare + Social Assistance	15.7%	15.6%	14.7%	9.6%	-0.9%
Retail Trade	13.0%	11.7%	10.7%	11.4%	-1.0%
Accommodation + Food Svcs.	10.7%	9.6%	6.3%	7.0%	-3.3%
Educational Svcs.	2.3%	9.3%	10.0%	5.1%	0.7%
Manufacturing	10.4%	9.3%	10.5%	16.5%	1.2%
Professional, Scientific, + Technical Svcs.	7.4%	6.7%	8.4%	9.5%	1.7%
Admin. + Support + Waste Management + Remediation Svcs.	7.3%	6.6%	4.6%	4.9%	-2.0%
Construction	5.6%	5.1%	7.4%	7.5%	2.3%
Finance + Insurance	4.9%	4.4%	5.3%	6.3%	0.9%
Transportation + Warehousing	4.1%	4.4%	5.1%	3.3%	0.7%
Wholesale Trade	4.9%	4.4%	2.5%	3.4%	-1.9%
Other Svcs. (exc. Public Administration)	3.7%	3.3%	5.1%	4.0%	1.8%
Information	2.3%	2.2%	2.1%	4.1%	-0.1%
Arts, Entertainment, + Recreation	1.8%	1.9%	2.0%	2.3%	0.1%
Management of Companies + Enterprises	1.9%	1.7%	0.1%	0.0%	-1.6%
Real Estate + Rental + Leasing	1.8%	1.6%	2.2%	1.8%	0.6%
Agriculture, Forestry, Fishing + Hunting	1.0%	0.9%	1.5%	0.8%	0.6%
Utilities	0.5%	0.6%	0.8%	0.5%	0.2%
Mining, Quarrying, + Oil + Gas Extraction	0.6%	0.5%	0.6%	2.0%	0.1%
Undefined	0.2%	0.1%	0.0%	0.0%	-0.1%

Note: Data are sorted by QCEW Jobs: Private + Public. QCEW Jobs: Private Only reflects available, complete 6D NAICS data utilized later in the analytics and report. It is also worth noting unlike QCEW, the CPS data above includes the self-employed, armed forces, and unpaid family workers. Because of rounding, deltas may not match those calculated from table values. Source: CPS DWS; dF-QCEW; Mass Economics analysis.

4.4 Arriving at Three Methods for Estimating Displacement in the Appalachian Region

The project replicated the previous study's approach for estimating displacement in Appalachia, calculating logistic weights to split DWS observations in the partial geographies into Appalachian Region and non-Appalachian Region portions. This method, which we refer to as the "worker characteristics" method, uses socioeconomic variables in the DWS to identify Appalachian Region and non-Appalachian Region portions of the partial geographies.

In this section, we lay out two new methods for identifying displacement in the Appalachian Region. The first method, which we refer to as the "separations and hires" method, uses QWI data at the county level to create rates of separations and hires in the Appalachian and non-Appalachian counties in each of the partial geographies. The ratio of separations and hires is used to split DWS observations into Appalachian Region and non-Appalachian Region portions.

The second method is referred to as the "industry mix" method. The industry mix method uses CPS-DWS to calculate detailed industry displacement rates at the national level for the industry from which the worker was displaced. These industry rates are applied to the QCEW jobs data at the corresponding 6-digit NAICS industry, then are aggregated to the total economy level for each county. Although this method is limited because it utilizes a national industry displacement rate to estimate local displacement, it addresses what we believe is a potential issue with the DWS survey: that displacement is geographically "spiky," and survey methods that do not account for this could underestimate total worker displacement.

4.5 New Method Using Separations and Hires

We use DWS data (as in the "worker characteristics" method) but create a new set of weights for the partial geographies. These weights use QWI separations-to-hires ratios. Separations reflect jobs that exist, then disappear, from one quarter to the next. Hires reflect a new record of an employee receiving earnings from an employer in a given quarter.[13] On their own, separations do not necessarily track displacement, and separations cover a broad landscape of jobs that are eliminated, including displacements as well as other types of separations. After trying several metrics — separations relative to employment, separations minus hires relative to employment, and the separations-to-hires ratio — we determined that the relationship between separations and hires generally tracks national displacement rates. (See Figure 1.)

13. See: "Quarterly Workforce Indicators 101: Local Employment Dynamics." n.d. https://lehd.ces.census.gov/doc/QWI_101.pdf.

Figure 1. Displacement and Separation Rates (Sep/Hire), U.S., 2011-2021

Source: CPS DWS; dF-QWI; Mass Economics analysis.

First, we calculate a separations-to-hires ratio for the Appalachian Region and non-Appalachian Region portions of the partial for each of the 3-year survey periods using QWI county-level data. We multiply these ratios by the stable employment in the Appalachian Region and non-Appalachian Region portions of the partial. Then, we calculate the Appalachian Region and non-Appalachian Region share of this product and use these shares to split the DWS observations in the partial. Since these data reflect place of work, we assume the same industry displacement profile for residents of the geography as for workers.

In the 2011-2021 period, the Appalachian Region had a similar displacement rate to the rest of the U.S. (2.3%). In earlier years (2011-2017), the Appalachian Region rates of displacement were higher than the rest of the U.S. In more recent years, the Appalachian Region rates fell below the rest of the U.S. (See Table 12.)[14] These trends largely track with the results using the worker characteristics method (see Table 5 in subsection 3.4).

14. Note: The state of Mississippi lags in QWI data, and data are not available for 2018 onward. For the 2017-2019 survey period, only 2017 MS data are used. For the 2019-2021 survey period, the overall ARC rate is estimated by using the same MS share of ARC for displaced workers, displaced not currently employed workers, and all workers as in the 2017-2019 period.

Table 12. Displacement in Appalachian Region and Rest of U.S. Using Separations and Hires

	APPALACHIAN REGION			REST OF U.S.			% POINT DELTA
Year	Total Jobs*	Estimated Number of Displaced Workers	Estimated Displacement Rate	Total Jobs*	Estimated Number of Displaced Workers	Estimated Displacement Rate	Appalachian Region – Rest of U.S.
2011-2013	10,678,100	338,100	3.2%	130,476,200	3,953,800	3.0%	0.1%
2013-2015	10,951,600	240,100	2.2%	135,200,100	2,951,200	2.2%	0.0%
2015-2017	11,451,200	274,700	2.4%	137,868,400	2,706,700	2.0%	0.4%
2017-2019	11,681,700	182,900	1.6%	141,610,200	2,489,300	1.8%	-0.2%
2019-2021	10,253,100	204,100	2.0%	138,978,700	3,338,400	2.4%	-0.4%
2011-2021	-	-	2.3%	-	-	2.3%	0.0%

Note: The 2011-2021 displacement rate reflects a weighted average of the five individual surveys.
Because of rounding, deltas may not match those calculated from table values.
*Includes displaced, not currently employed. Source: CPS DWS; dF-QWI; Mass Economics analysis.

4.6 New Method Using Industry Mix

For the industry mix method, we create detailed (6D NAICS) industry displacement rates from Census industry displacement information. First, we calculate national displacement rates for consistent vintages of Census industries in the 2014, 2016, 2018, 2020 and 2022 DWS surveys (see Table 46 through Table 51 in section 9.6 in the appendix for the top 10 Census industries in each time period). Second, we crosswalk 6D NAICS to consistent Census industries.

Third, we calculate three-year averages for county employment for 6D NAICS industries for the 2014 (2011-2013), 2016 (2013-2015), 2018 (2015-2017), 2020 (2017-2019) and 2022 (2019-2021) periods. Fourth, we apply national displacement rates by survey year to the 6-digit NAICS county data. Where available, the 6-digit rate is used; if this rate is not available, the sector-specific rate is used. For any sectors that are missing in the DWS data, we use the overall yearly displacement rate.[15] Fifth, we summarize the number of displaced workers at the total economy level.

15. Following the approach of the previous study, we calculate the displacement rate as the number of displaced workers divided by the sum of the number of currently employed workers and the number of displaced workers not currently employed. Some industries do not have observations for displaced workers not currently employed. Given that this is generally a (very) small share of the denominator—on average, <3% for observations with this information—we allowed these industries' displacement rates to be calculated in the same way. This occurs infrequently (affecting about 29% of industries that can be crosswalked to NAICS) and generally only occurs when the number of displaced worker observations is also small.

Finally, we calculate the geography's displacement rate as the number of displaced workers divided by the total workers. Using the industry mix approach, the Appalachian Region has a similar displacement rate to the rest of the U.S. throughout the 2011-2021 period, with slightly higher displacement rates in 2011-2013 and 2015-2017. (See Table 13.)

Table 13. Displacement in the Appalachian Region and Rest of U.S. Using Industry Mix

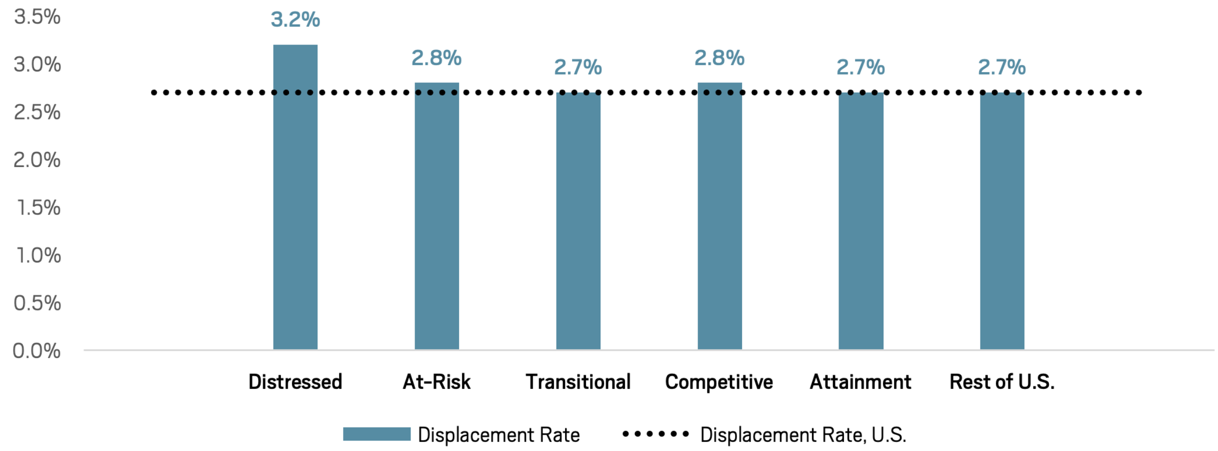
	APPALACHIAN REGION			REST OF U.S.			% POINT DELTA
Year	**Total Jobs**	**Estimated Number of Displaced Workers**	**Estimated Displacement Rate**	**Total Jobs**	**Estimated Number of Displaced Workers**	**Estimated Displacement Rate**	**Appalachian Region – Rest of U.S.**
2011-2013	7,814,000	276,000	3.5%	102,780,000	3,476,000	3.4%	0.1%
2013-2015	7,994,000	202,000	2.5%	107,616,000	2,641,000	2.5%	0.1%
2015-2017	8,164,000	209,000	2.6%	112,233,000	2,716,000	2.4%	0.1%
2017-2019	8,334,000	180,000	2.2%	116,096,000	2,523,000	2.2%	0.0%
2019-2021	8,149,000	245,000	3.0%	114,187,000	3,380,000	3.0%	0.0%
2011-2021 Average	8,091,000	222,000	2.7%	110,582,000	2,947,000	2.7%	0.1%

Note: Because of rounding, deltas may not match those calculated from table values.
Source: CPS DWS; dF-QCEW; Mass Economics analysis.

Because the industry mix data is at the county level it allows for more detailed geographic analyses than are possible with the other two methods. We can also leverage ARC's county-level economic typology groups (distressed, at-risk, transitional, competitive, attainment).[16] In the Appalachian Region, distressed counties are estimated to have a higher displacement rate (3.2%) than the other county types. (See Figure 2.) This suggests that in the 2011-2021 period, the distressed counties had an employment base that was more concentrated in high-displacement industries than was typical nationally.

16. See https://www.arc.gov/distressed-designation-and-county-economic-status-classification-system/ for an overview of ARC's economic typology.

Figure 2. Displacement Rate by County Economic Status FY24 in Appalachia, 2011-2021

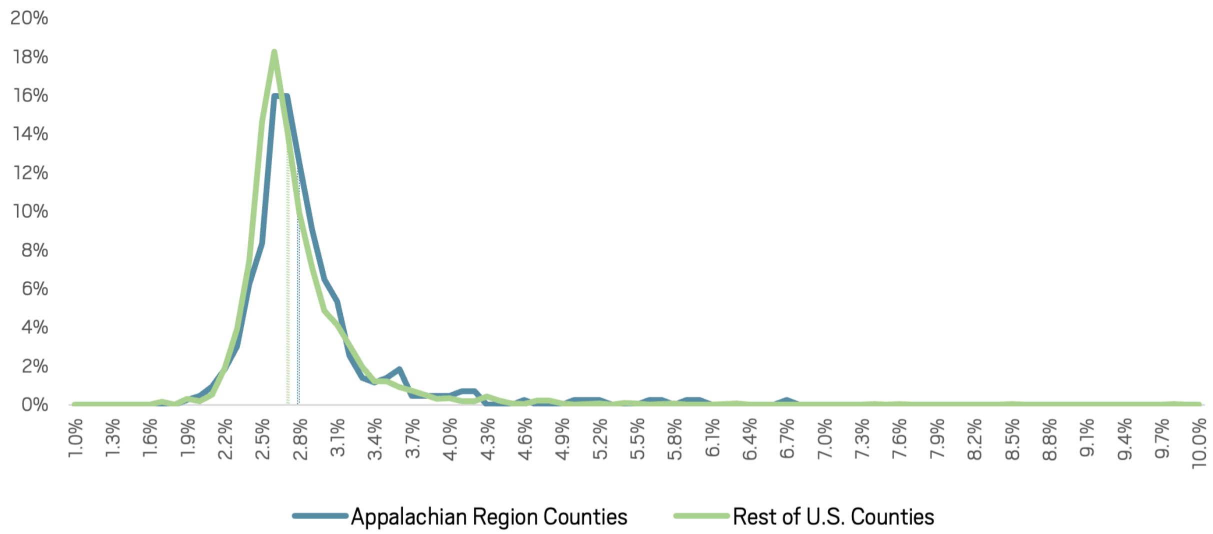


Source: CPS DWS; dF-QCEW; Mass Economics analysis.

Compared to counties in the rest of the U.S., displacement rates in Appalachian counties skew higher. (See Figure 3.) Nineteen percent of Appalachian Region counties have displacement rates above 3%, compared to 16.6% of counties in the rest of the U.S. Over half of these counties are classified as distressed or at-risk, suggesting that the industry mix in these counties makes them more vulnerable to displacement events.

Since distressed and at-risk counties tend to have the lowest populations across the five county types, lower population is also associated with higher displacement rates. Considering that the overall displacement rate in Appalachia is on par with the rest of the U.S., this suggests that a disproportionate share of counties in the Appalachian Region face more intense and/or more acute displacement pressures.

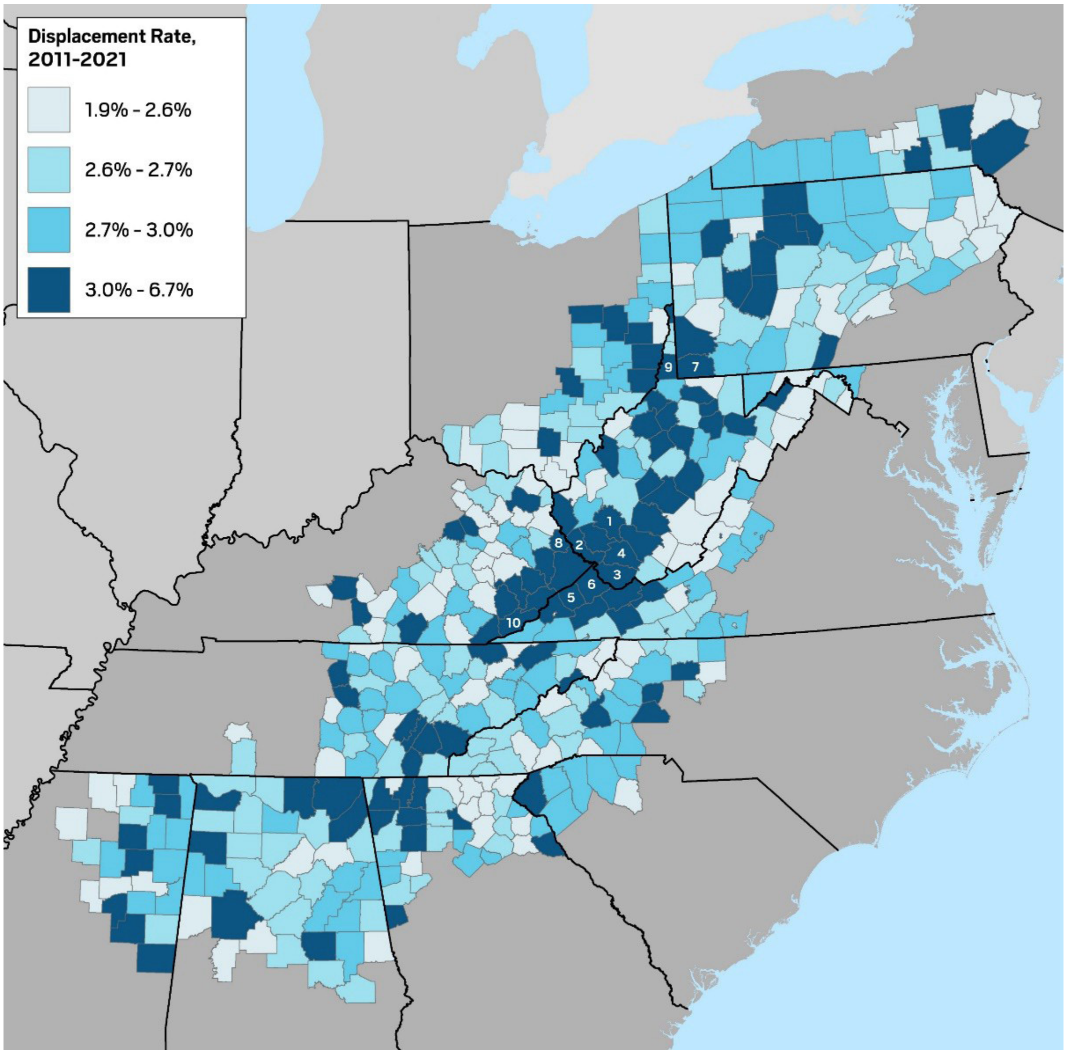
Figure 3. Percent of Counties by Displacement Rate, Appalachian Region and Rest of U.S. Counties, 2011-2021



Source: CPS DWS; dF-QCEW; Mass economics analysis.

When the county-level displacement rates are mapped using the industry mix method, a few patterns emerge. First, among the top ten Appalachian Region counties by estimated displacement rate, eight are classified as distressed under the FY 2024 economic status typology. These same eight counties are all clustered deep in Central Appalachia around the intersection of the West Virginia, Virginia and Kentucky borders. The other two counties in the top ten are "transitional" and adjacent to one another in Southwestern Pennsylvania and Northern West Virginia (see Figure 4). Together, these top ten counties make up 0.6% of total workers but 1.2% of displaced workers over the 2011-2021 time period.

Figure 4. Displacement Rate by County, Appalachian Region, 2011-2021



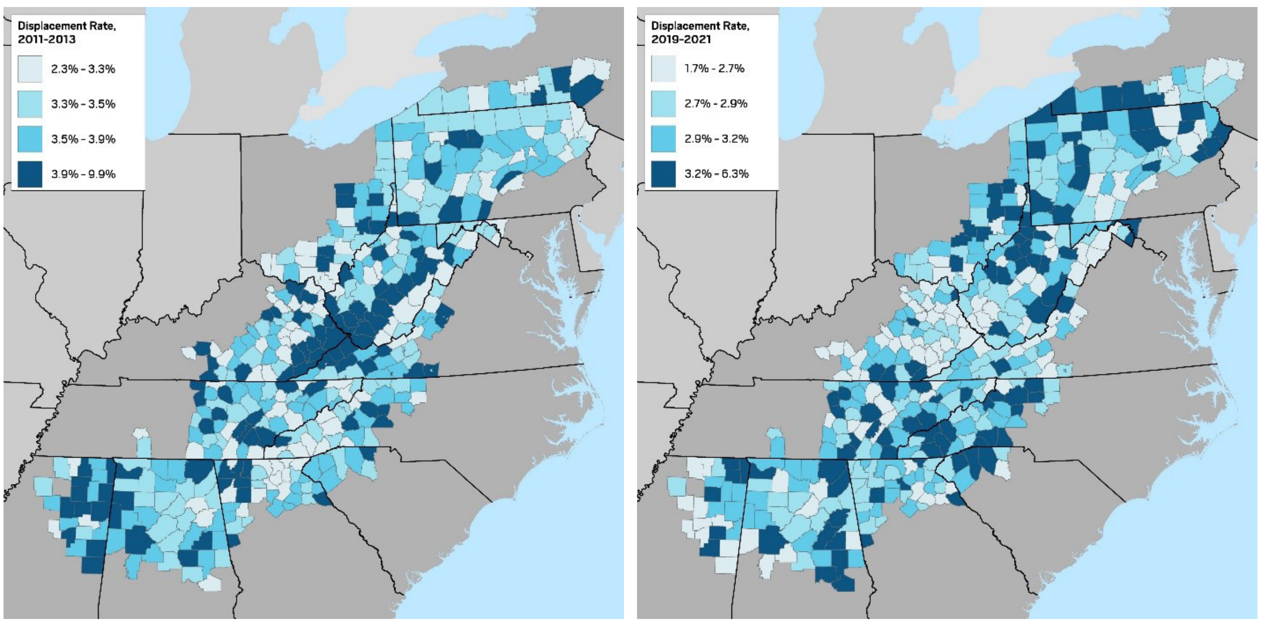
Rank	County	Economic Status, FY24	Estimated Displacement Rate
1	Boone County, WV	Distressed	6.7%
2	Mingo County, WV	Distressed	6.0%
3	McDowell County, WV	Distressed	5.9%
4	Wyoming County, WV	Distressed	5.7%
5	Dickenson County, VA	Distressed	5.6%
6	Buchanan County, VA	Distressed	5.2%
7	Greene County, PA	Transitional	5.1%
8	Martin County, KY	Distressed	5.0%
9	Marshall County, WV	Transitional	4.6%
10	Harlan County, KY	Distressed	4.2%

Source: CPS DWS; dF-QCEW; Mass Economics analysis.

As the economies and industry mixes of counties change over time, including from 2011-2021, the spatial pattern of county-level displacement rates also shift. (See Figure 5.) One longer term change is the relative improvement in the displacement rate in the previously noted cluster of counties around the intersection of the West Virginia, Virginia and Kentucky borders.

Figure 5. Displacement Rate Quartiles by County and 3-Year Periods, Appalachian Region, 2011-2013 and 2019-2021

2011-2013 2019-2021



Source: CPS DWS; dF-QCEW; Mass Economics analysis.

The top counties by displacement rate have also shifted over the years. Table 14 shows a distinct shift occurring in the top 10 counties between the 2015-2017 and 2017-2019 time periods. Specifically, the top eight counties during the overall 2011-2021 time period were consistently in the top 10 over the 2011-2013, 2013-2015, and 2015-2017 time periods. All the top 10 counties in these three time periods were — and still are — highly concentrated in coal mining, and national displacement rates in coal mining were also high over the same time periods. Starting in the 2017-2019 time period, the national displacement rate in coal mining declined significantly and a completely distinct set of counties rose to the top ten, driven by high national displacement rates in other industries. Over the full 2011-2021 period, there were 33 unique counties that were in the top 10 at some point.

Table 14. Counties with Top 10 Displacement Rates in Appalachian Region, 2011-2021

County	Rank 2011-2013	Rank 2013-2015	Rank 2015-2017	Rank 2017-2019	Rank 2019-2021	Rank 2011-2021
Boone County, WV	1	1	4	151	391	1
Mingo County, WV	3	2	1	79	363	2
McDowell County, WV	2	4	3	84	297	3
Wyoming County, WV	5	5	2	139	11	4
Dickenson County, VA	4	3	5	36	127	5
Buchanan County, VA	7	6	7	65	325	6
Greene County, PA	9	7	6	101	153	7
Martin County, KY	6	8	9	172	386	8
Marshall County, WV	12	9	11	34	57	9
Harlan County, KY	10	17	15	301	357	10
Choctaw County, MS	14	11	10	383	424	11
Taylor County, WV	117	14	8	85	368	12
Leslie County, KY	8	18	16	391	430	14
Ritchie County, WV	56	37	14	25	4	15
Murray County, GA	19	21	20	7	136	16
Webster County, WV	17	10	23	411	411	17
Doddridge County, WV	334	90	64	1	2	19
Smith County, TN	44	20	52	11	9	20
Covington City, VA	119	12	94	184	5	24
Meigs County, TN	50	25	28	2	394	26
DeKalb County, AL	225	293	41	174	1	28
Elbert County, GA	35	87	69	67	3	29
Heard County, GA	38	73	35	6	48	31
Gordon County, GA	36	48	30	10	219	33
Whitfield County, GA	41	41	37	9	271	35
Lewis County, WV	270	43	24	39	10	36
Gilmer County, WV	155	88	34	21	6	37
Perry County, OH	148	24	190	4	53	42
Elk County, PA	94	30	58	8	322	44
Metcalfe County, KY	32	84	317	3	123	45
Alcorn County, MS	163	273	48	86	8	53
Hart County, KY	49	307	65	5	336	58
Sevier County, TN	418	411	205	355	7	225

Source: CPS DWS; dF-QCEW; Mass Economics analysis.

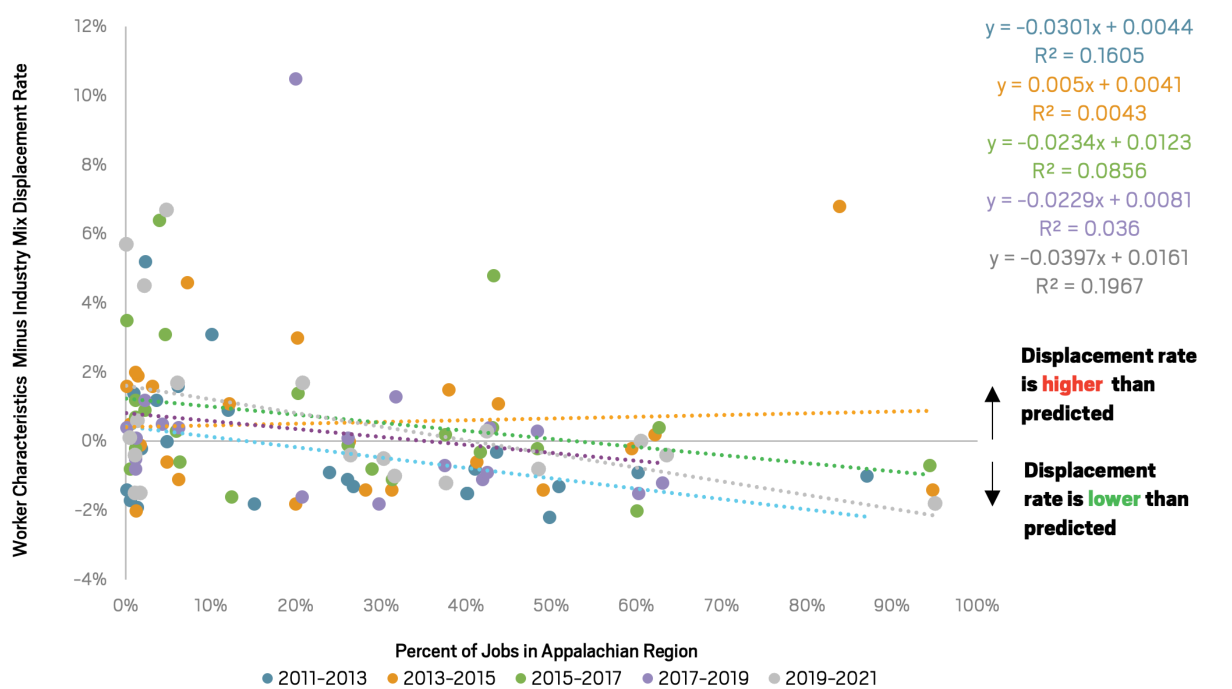
There are at least several known limitations to using DWS to develop these national industry profiles. First, there are questions about whether the DWS accurately captures displacement across industries. This is because the DWS is a reflection of the CPS sample, which is designed to represent the general U.S. population rather than the distribution of workers across specific industries. Second, there are small sample sizes by industry. To the greatest extent possible, we use all available industry data, but there are some cases where limited numbers of samples and/or missing observations for components of the displacement rate could introduce bias. Third, there is occasionally coarse industry detail, in part stemming from the fact that there are missing Census industries that correspond to "partial" industry coverage in the NAICS universe. Fourth, public and private sector coverage does not align with the private sector coverage of QCEW; this has a bigger impact on some sectors (e.g., Educational Services) than others. (See Table 11 above). Finally, DWS data are based on place of residence and

QCEW data are based on place of work; this does not affect national analyses but is a caveat for interpreting and comparing results at the sub-national level.

4.7 Closer Examination of the Partial Geographies

The partial geographies deserve special attention in interpreting these results because these are the geographies that cannot be cleanly identified in the DWS data. The industry mix approach showcases differences in displacement rates solely as a function of industry mix. In other words, a county with a higher displacement rate has a larger share of jobs in industries that have high displacement nationally. However, county characteristics, such as level of distress, could have an independent effect on displacement patterns. If there were an Appalachian Region effect, we would expect partials with a larger share of jobs in the Appalachian Region to also have higher differences between the DWS worker characteristics and industry mix displacement rates. Specifically, we would expect the DWS to reflect a higher displacement rate than what the industry mix alone would predict. We look for a positively correlated relationship between an increasing share of Appalachian jobs in the partial geographies and an increasing difference in the displacement rates. Testing across the partials in all five survey time periods shows low correlation values (R^2 ranged from .004 to 0.20) and a slight negative correlation. (See Figure 6.) This suggests that there is not an Appalachian Region-specific effect producing higher displacement rates.

Figure 6. Worker Characteristics Minus Industry Mix Displacement Rate vs. Percent of Jobs in Appalachian Region

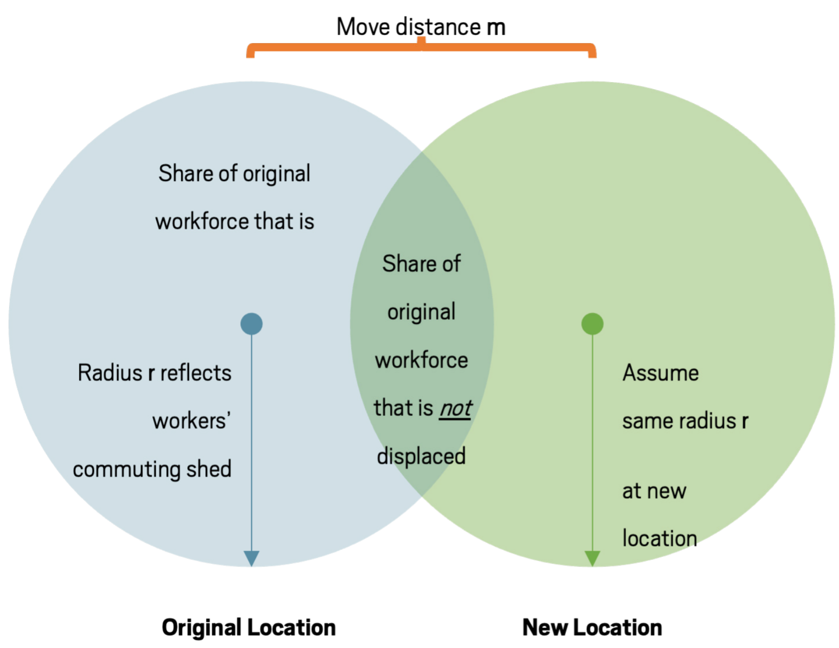


Note: Only includes partials where the displaced rate can be calculated from DWS.
Source: CPS DWS; dF-QCEW; Mass Economics analysis.

4.8 Deeper Dive: Using YTS Data to Understand Type 1 Displacement

Finally, we perform a deeper dive on Type 1 displacement using YTS data, which track establishment-level moves and closures. Type 1 displacement consists of moves and closures, both of which can be tracked in the YTS data. Closures are directly tracked in YTS, and each establishment has a field denoting “Last Year” in the event of a closure. When an establishment closes, it is assumed that 100% of workers at the closed establishment are displaced. Moves and move distance can be estimated using YTS data on establishments where the county code (FIPS) has changed over time. Each establishment is reported with a time series of FIPS. We compare FIPS in time and + 1; if different, we look up the distance between the counties’ geographic centers to determine the estimated distance of the move. To calculate an estimated share of workers displaced by the move, we use a simplified geometric worker commute shed, assuming a maximum commute distance, r, of 50 miles. (See Figure 7 and Table 15 and subsection 10.6 for additional methodological details.)

Figure 7. Schematic of Estimating the Share of Workers Displaced Due to an Establishment Move



We create buckets around move distance and average the share of workers retained (versus displaced) for moves within each bucket. (See Table 15.)

Table 15. Assumptions Around Workers Displaced as a Function of Move Distance (in Miles)

Minimum Miles	Maximum Miles	% Workers Retained	% Workers Displaced
0	10	93%	7%
10	20	81%	19%
20	30	69%	31%
30	40	56%	44%
40	50	45%	55%
50	60	34%	66%
60	70	24%	76%
70	80	15%	85%
80	90	7%	93%
90	100	2%	98%
100	∞	0%	100%

In order to assess how YTS-based Type 1 displacement aligns with the other methods, we compare the percent of Type 1 displacement in Appalachian partial geographies in the YTS, separations and hires, and worker characteristics methods using unweighted averages to capture the individual differences in each partial geography. On an unweighted average basis, the absolute difference between the percent of all Type 1 displacement in the Appalachian portion of the partials when comparing the YTS and the separations and hires method is less than one percentage point. (See Table 16.) Linear regression of YTS versus separations and hires share of Type 1 displacement across all partials is highly correlated (R^2 = .98). While the YTS and separations and hires methods are based on two distinct data sources, there are similarities: the separations and hires method and YTS data are both place of work-based, and both use a static share to split partial geographies based on actual Type 1 displacements in Appalachian Region counties in each partial. In contrast, the worker characteristics method is place of residence-based, and splits the partials based on the probability an observation is in the Appalachian Region. Since YTS tracks closely with the separations and hires method across the partials, it could be a tool for exploring more granular geographic information about Type 1 displacement in the Appalachian Region.

Table 16. Percent of Type 1 Displacement in Appalachian Region

	PERCENT OF TYPE 1 DISPLACEMENT IN APPALACHIAN REGION PARTIAL GEOGRAPHIES				
Survey Year	**YTS (Unwtd. Avg.)**	**Worker Characteristics Method (Unwtd. Avg.)**	**Separations and Hires Method (Unwtd. Avg.)**	**YTS Minus Worker Characteristics Method (Unwtd. Avg)**	**YTS Minus Separations and Hires Method (Unwtd. Avg.)**
2014	24.1%	35.8%	24.1%	-11.6%	0.0%
2016	23.1%	29.6%	22.5%	-6.5%	0.7%
2018	33.6%	40.4%	33.9%	-6.8%	-0.3%
2020	27.6%	34.6%	27.8%	-7.0%	-0.2%
2022	27.5%	39.3%	27.4%	-11.9%	0.1%

Note: In 2014, partials reflect the June 2006 definitions; in 2016-2022, partials reflect the February 2013 definitions.
Because of rounding, deltas may not match those calculated from table values.
Source: CPS DWS; dF-QCEW; YTS; Mass Economics analysis.

As a deeper dive into the dynamics surrounding establishment moves out of the Appalachian Region, we analyze the time series of establishments located in the Appalachian Region between 2011 and 2021, focusing on establishments that move from an Appalachian county to a county outside of the region. Between 2011 and 2021, approximately 1,500 establishments moved out of the Appalachian Region. Of those, 50 had at least 100 jobs in the year of the move. The average move distance for all establishments was about 70 miles and the median was 28 miles. These numbers were higher for establishments with at least 100 jobs in the year of the move (average of 122 miles, median of 68 miles). We estimate that these moves displaced more than half of the workers at these establishments (57% of workers overall; 61% for establishments with at least 100 jobs).

The industries with the most establishment moves out of the Appalachian Region from 2011 to 2021 are Services to Buildings and Dwellings, Building Equipment Contractors, and Legal Services. (See Table 17.) The two industries displacing the most workers due to moves over the same time period were Agencies, Brokerages, and Other Insurance Related Activities; and Commercial and Service Industry Machinery Manufacturing. (See Table 18.)

Table 17. Top 10 Industries for Establishment Moves Out of the Appalachian Region, 2011-2021

4-Digit NAICS	Description	Number of Moves	Average Distance of Move (Miles)
5617	Services to Buildings and Dwellings	68	61
2382	Building Equipment Contractors	49	69
5411	Legal Services	44	81
2361	Residential Building Construction	40	29
5242	Agencies, Brokerages, and Other Insurance Related Activities	39	63
8131	Religious Organizations	37	85
7225	Restaurants and Other Eating Places	36	57
5416	Management, Scientific, and Technical Consulting Services	35	67
2381	Foundation, Structure, and Building Exterior Contractors	33	53
5413	Architectural, Engineering, and Related Services	32	83

Source: YTS; Mass Economics analysis.

Table 18. Top 10 Industries for Establishment Moves Out of the Appalachian Region by Est. Number of Displaced Workers, 2011-2021

4-Digit NAICS	Description	Est. Number of Displaced Workers	Average Distance of Move (Miles)
5242	Agencies, Brokerages, + Other Insurance Related Activities	1,700	63
3333	Commercial + Service Industry Machinery Manufacturing	1,300	148
3371	Household + Institutional Furniture + Kitchen Cabinet Manufacturing	800	164
4451	Grocery Stores	600	95
4231	Motor Vehicle + Motor Vehicle Parts + Supplies Merchant Wholesalers	400	182
5511	Management of Companies + Enterprises	400	150
3335	Metalworking Machinery Manufacturing	400	159
4236	Household Appliances + Electrical + Electronic Goods Merchant Wholesalers	400	85
3222	Converted Paper Product Manufacturing	400	479
5411	Legal Services	300	81

Source: YTS; Mass Economics analysis.

Over the 2011-2021 time period, the YTS data indicate there were approximately 724,000 establishment closures in the Appalachian Region, representing about 6% of all establishment closures in the U.S. The industries with the most establishment closures in the Appalachian Region are Restaurants and Other Eating Places, Personal Care Services, and Residential Building Construction. (See Table 19.) The industries displacing the most workers from 2011 to 2021 due to closures were Restaurants and Other Eating Places, Federal Gov Executive, Legislative, and Other General Government Support, and Elementary and Secondary Schools. (See Table 20.)

Table 19. Top 10 Industries for Establishment Closures in the Appalachian Region, 2011-2021

4-Digit NAICS	Description	Number of Closures	Est. Number of Displaced Workers
7225	Restaurants and Other Eating Places	31,200	311,000
8121	Personal Care Services	22,700	70,000
2361	Residential Building Construction	21,600	84,000
6213	Offices of Other Health Practitioners	21,200	55,000
5242	Agencies, Brokerages, and Other Insurance Related Activities	20,900	77,000
8131	Religious Organizations	20,600	57,000
8111	Automotive Repair and Maintenance	16,800	50,000
5617	Services to Buildings and Dwellings	16,800	76,000
5419	Other Professional, Scientific, and Technical Services	15,300	49,000
2382	Building Equipment Contractors	15,000	77,000

Source: YTS; Mass Economics analysis.

Table 20. Top 10 Industries for Number of Displaced Workers due to Establishment Closures in the Appalachian Region, 2011-2021

4-Digit NAICS	Description	Est. Number of Displaced Workers	Number of Closures
7225	Restaurants and Other Eating Places	311,000	31,200
9211	Federal Gov Executive, Legislative, and Other General Gov Support	107,000	11,100
6111	Elementary and Secondary Schools	106,000	3,800
6211	Offices of Physicians	89,000	12,000
2361	Residential Building Construction	84,000	21,600
4451	Grocery Stores	80,000	8,900
2382	Building Equipment Contractors	77,000	15,000
5242	Agencies, Brokerages, and Other Insurance Related Activities	77,000	20,900
5617	Services to Buildings and Dwellings	76,000	16,800
8121	Personal Care Services	70,000	22,700

Source: YTS; Mass Economics analysis.

4.9 Comparing the Previous Study's Approach to this Approach

In this study, we have estimated three sets of displacement rates: worker characteristics, separations and hires, and industry mix. Generally, the industry mix-based rate produces the highest rates, both in the Appalachian Region and the rest of the U.S. (See Table 21.)

Table 21. Three Sets of Displacement Rates

	APPALACHIAN REGION			REST OF U.S.		
Year	Worker Characteristics	Separations and Hires	Industry Mix	Worker Characteristics	Separations and Hires	Industry Mix
2011–2013	3.2%	3.2%	3.5%	3.0%	3.0%	3.4%
2013–2015	2.2%	2.2%	2.5%	2.2%	2.2%	2.5%
2015–2017	2.4%	2.4%	2.6%	2.0%	2.0%	2.4%
2017–2019	1.6%	1.6%	2.2%	1.8%	1.8%	2.2%
2019–2021	2.1%	2.0%	3.0%	2.4%	2.4%	3.0%
2011–2021	2.3%	2.3%	2.7%*	2.3%	2.3%	2.7%*

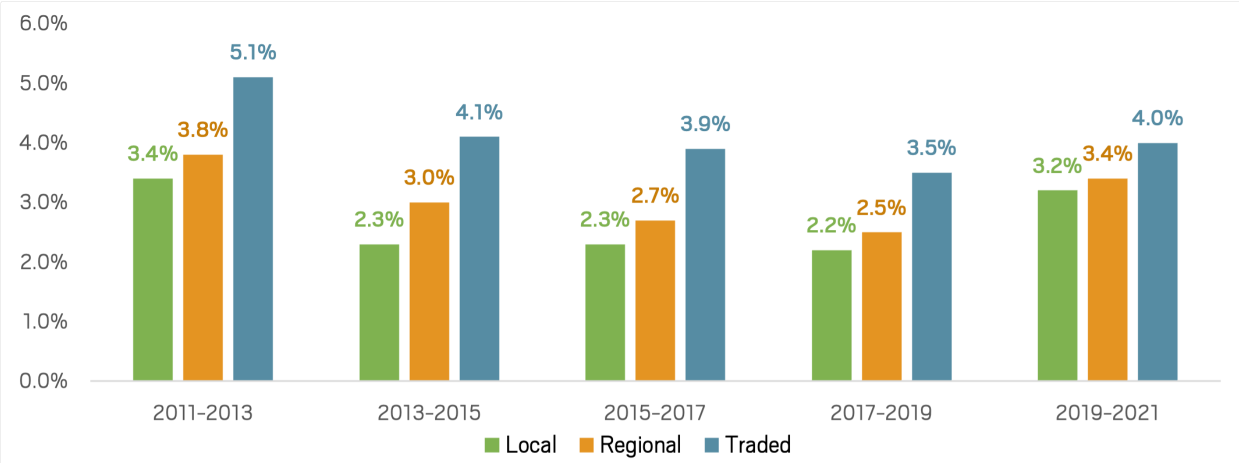
*The overall rates are expected to be slightly higher for the industry mix approach because we are not pooling the entire denominator of workers as in the CPS-based approach. The remainder of the difference could also be suggestive of DWS under-sampling workers in high-displacement industries.

Source: CPS DWS; dF-QCEW; dF-QWI; Mass Economics analysis.

We speculate that this is because the DWS under-samples workers in industries with high displacement rates. Using the market area of the industry as an example: Local industries serve local geographies (individual counties, towns and neighborhoods) and tend to be consumer-oriented; regional industries serve markets across multiple counties within a metropolitan area and typically are business-to-business (B2B) industries; and traded industries serve national and global market areas and, across the U.S., regions specialize in different traded industries based on local assets, costs and history.[17] We find that traded industries, which are geographically concentrated and spiky by nature, tend to have higher displacement rates (even using DWS data, which may "miss" some of these traded industries in its broad, national sampling). (See Figure 8.)

17. See Lynch, T. M., & Manduca, R. (2024). Beyond Local and Traded: Evidence for a Third Industry Market Area Type and Implications for Regional Economic Development. Economic Development Quarterly, 38 (3), 183-194.

Figure 8. Average Displacement Rates by Survey Period and Market Area of Industry



Source: CPS DWS; Mass Economics analysis.

4.10 Benefits and Drawbacks to This Approach

This approach, which consists of the separations and hires ratio applied to the DWS data and the industry mix methods both have some drawbacks. The separations and hires method only uses a static Appalachian/non-Appalachian share for the survey period, which may be overly simplistic. By comparison, the worker characteristics method considers the socioeconomic variables available in each observation in a given partial in the CPS and DWS data and could be considered more specific because of these additional data points. The industry mix method relies on the national industry displacement rates, which could be biased given small sample sizes, especially in a way that provides poor coverage of geographically spiky industries. It also assumes that local displacement matches national displacement conditions, although we know that displacement rates do vary by geography even after controlling for industry mix.

However, new methods offer key benefits compared to the worker characteristics approach used in the previous study. Rather than relying on CPS socioeconomic variables and estimating logit models for the partial geographies, the separations and hires approach uses a separate source of information on the Appalachian Region's share of displacements (as proxied by separations and hires) in order to split DWS observations into Appalachian and non-Appalachian portions. This method brings a computational advantage in that we avoid having to estimate logit models for 60 partial geographies, and it's also beneficial in that there are other insights that can be gleaned from the QWI time series. The industry mix method is beneficial because it develops the most geographically specific (county-level) estimates of displacement using national industry displacement rates. It is also computationally advantageous, provides insights on the industry drivers of displacement and is well-suited to a sub-national study such as this one, where the multi-state geography of the Appalachian Region requires county-specific data.

5. CHARACTERISTICS OF DISPLACED WORKERS

5.1 Overview

The following analysis explores DWS variables for the Appalachian Region, the rest of the U.S. and metro and nonmetro portions of the Appalachian Region and the rest of U.S. It also uses QWI data to examine the displacement impacts on different demographic groups and examine the extent to which different groups are affected by displacement in different geographies and industries.

5.2 Data Sources

This analysis leverages the CPS DWS data, as well as QWI for 2021.[18]

5.3 Analysis of DWS Variables for Appalachian Region and Rest of U.S.

In earlier stages of this work, the project team replicated some of the displacement analysis performed by the researchers of the previous study. In this task, we provide more coverage of these data and show, where possible, information that compares metro and nonmetro areas in the Appalachian Region and the rest of the U.S. In this section, percents are based on the logistic weights developed for the worker characteristics method, and the 2011-2021 period is used to maximize the number of available observations in the DWS data.

Type of Displacement

Type 1 displacement (moves and closures) disproportionately affects the Appalachian Region. 42% of displaced workers in the Appalachian Region were displaced due to Type 1 displacement compared to 37% in the rest of the U.S. Generally, Type 1 displacement rates are higher in nonmetro than metro areas, while the opposite is true for Type 2 displacement (insufficient work).

18. Mississippi data are known to lag behind current data releases in QWI, so we use the latest year of data (2017) for Mississippi.

Table 22. Summary of DWS Variables (Logistic Weights): Type of Displacement

Variable	Response	OVERALL Appalachian Region	OVERALL Rest of U.S.	METRO AREAS Appalachian Region	METRO AREAS Rest of U.S.	NONMETRO AREAS Appalachian Region	NONMETRO AREAS Rest of U.S.
Type of Displacement	Type 1: Plant or company closed or moved	42%	37%	39%	36%	48%	43%
	Type 2: Plant or company operating but lost/left job because of insufficient work	27%	28%	28%	29%	25%	27%
	Type 3: Plant or company operating but lost/left job because position or shift abolished	31%	35%	33%	35%	27%	30%

Source: CPS DWS; Mass Economics analysis.

Given Notice for Loss of Job

Displaced workers in the Appalachian Region — both overall and in metro areas — are more likely to receive no notice regarding their lost job compared to the rest of the U.S. (unlike in nonmetro areas). Displaced Appalachian workers in nonmetro areas are more likely to receive than those in the metro areas, while the pattern is the opposite in the rest of the U.S. Displaced Appalachian workers are more likely to receive less than one month's notice for the loss of their job compared to the rest of the U.S., and this was more likely in Appalachian nonmetro areas, while there was no difference between metro and nonmetro areas in the rest of the U.S.

Table 23. Summary of DWS Variables (Logistic Weights): Given Notice for Loss of Job

Variable	Response	OVERALL Appalachian Region	OVERALL Rest of U.S.	METRO AREAS Appalachian Region	METRO AREAS Rest of U.S.	NONMETRO AREAS Appalachian Region	NONMETRO AREAS Rest of U.S.
Given Notice for Lost Job	No	59%	57%	60%	56%	57%	59%
	Yes	41%	43%	40%	44%	43%	41%
How Much Notice was Given for Loss of Job	<1 month	33%	28%	30%	28%	37%	31%
	1-2 months	25%	36%	25%	36%	26%	35%
	2+ months	42%	36%	45%	36%	37%	34%

Source: CPS DWS; Mass Economics analysis.

Tenure, Hours of Last Job, and Years Since Displacement

Most displaced workers spent 3-10 years at their lost job. The share in the Appalachian Region (67%) was slightly lower than in the rest of the U.S. (70%). In Appalachia, displaced workers in nonmetro areas tend to have longer tenure than displaced workers in metro areas: 17% in nonmetro Appalachia had worked at their previous employer for 21 or more years, compared to 13% in the rest of nonmetro U.S. and 12% in metro Appalachia. Almost all displaced workers were full-time at their lost job, though the shares were consistently slightly higher among Appalachian workers.

Table 24. Summary of DWS Variables (Logistic Weights): Tenure, Hours of Last Job, and Years Since Displacement

		OVERALL		METRO AREAS		NONMETRO AREAS	
Variable	Response	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.
Tenure (Length of Time Worked at Lost Job)	3 to 10 Years	67%	70%	69%	71%	62%	69%
	11 to 20 Years	19%	20%	19%	20%	21%	17%
	21+ Years	14%	10%	12%	9%	17%	13%
Worked Full Time Hours at Lost Job	No	8%	10%	7%	10%	10%	13%
	Yes	86%	85%	88%	86%	84%	82%
	Hours Varied	6%	4%	5%	4%	6%	5%
Years Since Last Worked at Lost Job	Last Year	38%	36%	34%	36%	45%	38%
	2 Years Ago	35%	35%	37%	35%	30%	33%
	3 Years Ago	27%	29%	29%	29%	24%	29%

Source: CPS DWS; Mass Economics analysis.

Unemployment Benefits and Health Insurance

Slightly more than half of the Appalachian Region's displaced workers did not receive unemployment benefits. Only in the Appalachian Region's nonmetro areas are displaced workers more likely to have received unemployment benefits (52%), opposite the rest of the U.S., where nonmetro displaced workers were less likely to have received unemployment benefits (only 43%). With respect to the exhaustion of unemployment benefits, more than half of displaced workers do not know if their unemployment benefits were exhausted. However, among the remaining displaced workers, those in the Appalachian Region's nonmetro areas are less likely than those in the nonmetro areas in the rest of the U.S. to have exhausted their unemployment benefits (40% vs. 46%).

Across the U.S., displaced workers are more likely to have health insurance now than in their lost job, but the difference is 10 percentage points in the Appalachian Region (68% have health insurance at their current job versus only 58% had health insurance at their lost job) as compared to less than 7 percentage points in the rest of the U.S. (67% have health insurance at their current job versus only 60% had health insurance at their lost job). In the Appalachian Region, nonmetro displaced workers are more likely to have health insurance than those in metro areas, this is true for both their lost job (5 percentage points more) and their current job (8 percentage points more).

Table 25. Summary of DWS Variables (Logistic Weights): Unemployment Benefits and Health Insurance

		OVERALL		METRO AREAS		NONMETRO AREAS	
Variable	**Response**	**Appalachian Region**	**Rest of U.S.**	**Appalachian Region**	**Rest of U.S.**	**Appalachian Region**	**Rest of U.S.**
Received Unemployment Benefits	No	51%	53%	53%	52%	48%	57%
	Yes	49%	47%	47%	48%	52%	43%
Exhausted Unemployment Benefits	No	25%	23%	22%	24%	30%	22%
	Yes	22%	23%	23%	23%	20%	19%
	Unknown	53%	54%	55%	53%	50%	59%
Health Insurance at Lost Job	No	42%	40%	40%	39%	45%	42%
	Yes	58%	60%	60%	61%	55%	58%
Health Insurance at Current Job	No	32%	33%	29%	33%	37%	35%
	Yes	68%	67%	71%	67%	63%	65%

Source: CPS DWS; Mass Economics analysis.

Class of Worker and Industry

The vast majority (over 90%) of displaced workers are from the private sector. Generally, more workers are displaced from service industries (68% and 73% in the Appalachian Region and U.S., respectively) than goods-producing industries. Displaced workers in nonmetro areas, however, are more likely to have been displaced from a goods-producing industry than their metro area counterparts. Displaced workers in nonmetro Appalachia are more likely to have been employed in a goods-producing industry (42%) than displaced workers in metro Appalachia (26%) and the nonmetro rest of the U.S. (35%). Conversely, about three-fourths of displaced workers in metro areas (74% in the Appalachian Region and 75% in the rest of the U.S.) are displaced from service industries.

Table 26. Summary of DWS Variables (Logistic Weights): Class of Worker and Industry

		OVERALL		METRO AREAS		NONMETRO AREAS	
Variable	Response	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.
Class of Worker for Lost Job	Private	94%	92%	94%	93%	93%	89%
	Public	6%	8%	6%	7%	7%	11%
Industry of Lost Job (excl. Public Admin.)	Goods-Producing	32%	27%	26%	25%	42%	35%
	Services	68%	73%	74%	75%	58%	65%

Source: CPS DWS; Mass Economics analysis.

Work Since Job Loss and Current Labor Force Status

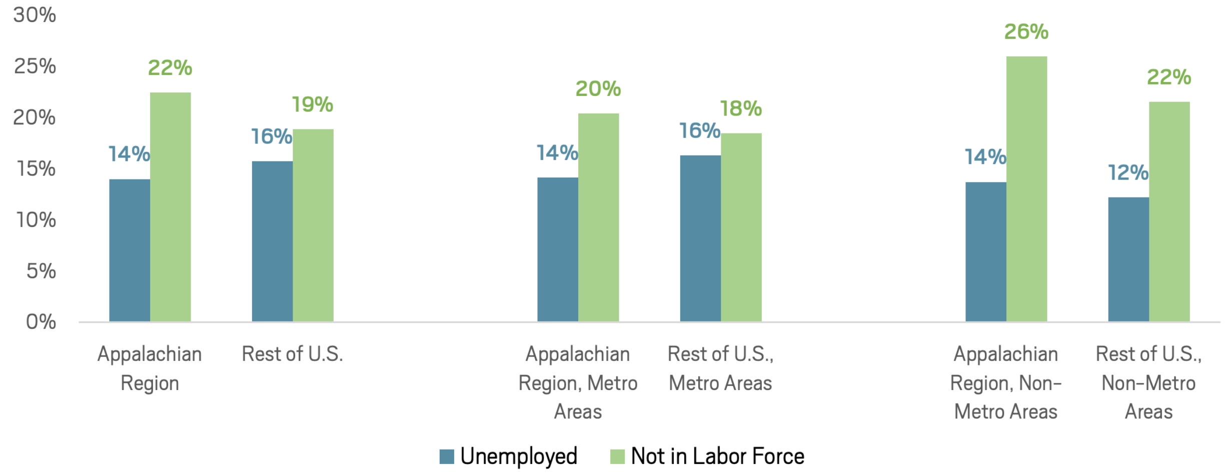
Overall and in metro areas, the percent of displaced workers who have not worked since job loss is similar in the Appalachian Region (32% overall, 31% in metro areas) and the rest of U.S. (31% in both). However, displaced workers in nonmetro Appalachia are more likely to have not worked since job loss (33%) than their counterparts in the rest of U.S. (29%). In nonmetro areas, among displaced workers who are now working at a new job, workers are more likely to start a job within six weeks than those in metro areas (52% in nonmetro Appalachia versus 44% in metro Appalachia). As for current labor force status, displaced workers in nonmetro Appalachia are more likely not to be in the labor force (26%) compared to those in nonmetro rest of the U.S. (22%) and to those in metro Appalachia (20%).

Table 27. Summary of DWS Variables (Logistic Weights): Work Since Job Loss and Current Labor Force Status

		OVERALL		METRO AREAS		NONMETRO AREAS	
Variable	Response	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.	Appalachian Region	Rest of U.S.
Worked Since Job Loss	No	32%	31%	31%	31%	33%	29%
	Yes	68%	69%	69%	69%	67%	71%
Number of Weeks Not Working Between End of Lost/Left Job and Start of Next Job	0 to 6	47%	47%	44%	46%	52%	52%
	7 to 13	17%	16%	18%	16%	15%	16%
	14 to 26	16%	14%	19%	14%	11%	11%
	27 to 39	5%	6%	4%	6%	6%	7%
	40 to 52	6%	9%	5%	9%	7%	6%
	53+	9%	9%	9%	9%	10%	8%
Current Labor Force Status	Employed	64%	65%	65%	65%	60%	66%
	Unemployed	14%	16%	14%	16%	14%	12%
	Not in Labor Force	22%	19%	20%	18%	26%	22%

Source: CPS DWS; Mass Economics analysis.

Figure 9. Current Labor Force Status in Appalachian Region and Rest of U.S., 2011-2021



Source: CPS DWS; Mass Economics analysis.

Weekly Earnings at Lost and Current Job

Generally, wages are lower in nonmetro areas than in metro areas for both lost and current jobs. Displaced workers in the Appalachian Region are less likely to earn more than $600 per week (real 2022 $) in their current job than displaced workers in the rest of the U.S. Across all geographies, displaced workers are less likely to earn more than $600 per week (real 2022$) in their current job than they were in their lost job. These declines are notably more dramatic in the nonmetro portions of the Appalachian Region and the rest of the U.S. compared to their respective metro portions.

Table 28. Summary of DWS Variables (Logistic Weights): Weekly Earnings at Lost and Current Job

		OVERALL		METRO AREAS		NONMETRO AREAS	
Variable	**Response**	**Appalachian Region**	**Rest of U.S.**	**Appalachian Region**	**Rest of U.S.**	**Appalachian Region**	**Rest of U.S.**
Weekly Earnings at Lost Job (Real 2022 $)	<$400	13%	12%	11%	11%	16%	15%
	$400-$600	14%	13%	12%	13%	17%	16%
	$600+	73%	75%	77%	76%	66%	69%
Weekly Earnings at Current Job (Real 2022 $)	<$400	18%	16%	14%	15%	26%	20%
	$400-$600	19%	16%	18%	15%	21%	20%
	$600+	62%	68%	67%	70%	53%	60%
Delta (Current - Lost)	<$400	5%	4%	4%	4%	9%	5%
	$400-$600	5%	3%	6%	2%	4%	4%
	$600+	-11%	-7%	-10%	-6%	-13%	-10%

Source: CPS DWS; Mass Economics analysis.

6. CONCLUDING REMARKS

This study has expanded the work of the previous study to investigate the prospects for using industry-based, public and private data sources to analyze worker displacement in the Appalachian Region. There are several important takeaways:

- **Implications for data and methods:** Other sources of federal data (e.g., QWI, BDS) can provide insights as to the number, type and intensity of displacement events, in direct form or as proxy. However, it is important to consider the universe of the underlying data and its comparability with DWS. Data suppression in some sources (e.g., QWI), as well as the need to convert the Census industries to NAICS codes, limited the level of industry detail possible in the partial geography analysis.
- **Implications for policy development in the Appalachian Region:** In calculating county-level displacement rates, it is possible to provide greater insights on individual counties, as well as the counties by economic status. This analysis revealed that distressed counties face higher displacement rates and that there may be disparate impacts for certain demographic groups in these counties. Policy interventions should be developed to address the specific needs of these places and to provide targeted supports for disproportionately impacted groups.
- **Possible areas for future research:** Several potential streams of research emerged that could build on and expand our understanding of displacement in the Appalachian Region. For example, understanding industry, not only worker, outcomes related to displacement could illuminate the sources and consequences of displacement. One hypothesis is that displacement signals short- and long-term industry decline. Displacement rates within a given geography may remain relatively stable over time, as industries experiencing high displacement may shrink or disappear, only to then be replaced by other industries also in decline. Another field for future research could further leverage the YTS data in order to explore sub-county level patterns of displacement by industry (e.g., within specific towns, districts, or corridors) and/or to develop a deeper understanding of establishment moves by geography (e.g., mapping moves to and from specific counties across the U.S. or quantifying intra-Appalachian Region moves).

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APPENDICES

8. APPENDIX FROM LITERATURE REVIEW

The project team identified several other relevant data sets that could prove valuable to worker displacement studies, even though they were not used by the displacement studies covered in this review. They are discussed in more detail below.

Mass Layoff Statistics (MLS) Program. Though this program has since ended, the Bureau of Labor Statistics Mass Layoff Statistics (MLS) program compiled and published data on mass layoffs. These events capture "establishments [with] at least 50 initial claims for unemployment insurance (UI) filed against them" over five weeks ("Mass Layoff Statistics," n.d.). Data are available from 1995 to 2012 at the county level by race, ethnicity, sex, and age, and reflect place of residence. These data could be used to understand Type 3 displacement.

Quarterly Census of Employment and Wages (QCEW). QCEW data are provided by the Bureau of Labor Statistics. As discussed earlier, these data are derived from state-collected unemployment insurance records, and they provide employment and wage data for detailed, six-digit North American Industry Classification System (NAICS) codes down to the county level ("Quarterly Census of Employment and Wages" 2022). These data can be paired with YTS establishment-level data and/or QWI (discussed below) to inform analysis of all three types of displacement.

Quarterly Workforce Indicators (QWI). QWI data are provided by the U.S. Census Bureau. They provide employment and wage data for four-digit NAICS codes down to the county level, with additional information on firm age, firm size, worker characteristics (i.e., sex and age, sex and education, race and ethnicity), and measures of employment change throughout the quarter (e.g., beginning of quarter employment, end of quarter employment, individual- and firm-level employment change) ("Quarterly Workforce Indicators 101: Local Employment Dynamics" 2019). By using county-level hiring and separation rates to understand the extent of churn in the local economy, these data can be used to inform analysis of Type 3 displacement.

Worker Adjustment and Retraining Notification Act. The WARN (Worker Adjustment and Retraining Notification) Act was created in 1988 and enacted in 1989. It requires employers to give workers facing displacement events (e.g., mass layoffs, plant closures) at least 60 days' notice, allowing them to find other employment and seek additional training or education, if necessary. The WARN Act only applies to private businesses or quasi-public entities that employ at least 100 full-time workers. WARN can be triggered by several large-scale, job-threatening events,[19] but there are several circumstances under

19. For example, if the business terminates employment for at least 500 full-time workers at one location, if there is a mass layoff event ("between 50 and 499 full-time workers" at one location are laid off, amounting to one-third of the full-time workers at that location), or if there is a plant closing ("a facility or operating unit within a single site of employment" is closed and 50 or more workers lose their jobs).

which businesses are not required to provide 60 days' notice[20] (Collins 2012; Bolle 1993; "Worker Adjustment and Retraining Notification (WARN) Act: Worker's Guide to Advance Notice of Closings and Layoffs" 2003). Some states have their own WARN laws that apply to smaller-scale events that otherwise would not trigger the federal WARN Act.[21]

State departments of labor generally compile and publish WARN notices,[22] often as part of their dislocated worker programs, but there is no federal collection of WARN notices. There are also third-party data sources that compile and publish state-level WARN data.[23] Data on WARN notices directly capture establishment/point-level Type 1 and/or Type 3 displacement events, with the added benefit that – despite lacking a centralized federal repository of WARN notices – all states must follow at least the minimum federal thresholds and standards for defining a mass layoff. There are some states (and, in some cases, local governments) that have their own additional WARN laws.[24] However, WARN notices provide little to no information on the lead-up to these events, making it hard, if not impossible, to use them to track Type 2 displacement events. It is also worth noting that previous studies have found incongruities between the WARN notice data and other data on mass layoffs and plant closings (GAO 2003).

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20. Includes unforeseen business circumstances (e.g., supply chain disruption, loss of a huge client); natural disasters; and "faltering companies" (where the advance notice warranted by WARN could jeopardize the company's "ability to find the capital or business it needs to continue operating").

21. California, Illinois, New Jersey, New York, and Tennessee all have state-level WARN laws with more stipulations than the federal WARN Act. See: https://www.employmentlawhandbook.com/employment-and-labor-laws/topics/layoff-notice-laws/.

22. See, e.g., https://dol.ny.gov/warn-notices; https://www.illinoisworknet.com/LayoffRecovery/Pages/ArchivedWARNReports.aspx.

23. See, e.g., https://layoffdata.com/; https://www.warntracker.com.

24. Jennings, Noah. 2022. "ANALYSIS: As Layoffs Rise, Employers Must Heed State WARN Laws." Bloomberg Law. December 12, 2022. https://news.bloomberglaw.com/bloomberg-law-analysis/analysis-as-layoffs-rise-employers-must-heed-state-warn-laws.

9. APPENDIX FROM REPLICATING THE PREVIOUS STUDY'S APPROACH

9.1 Overview

This document provides a detailed description of the process for replicating the previous study's approach (the "worker characteristics" method) to analyzing worker displacement in Appalachia in recent years.

9.2 Data Sources

This task relies on three data sources: the Displaced Worker Supplement (DWS) data to the Current Population Survey (CPS), CPS data, and American Community Survey (ACS) Public Use Microdata (ACS microdata). All were acquired from the Minnesota Population Center through usa.ipums.org and cps.ipums.org. Below is a brief description of each.

DWS data

The DWS data are the key data source for analyzing displacement incidence, characteristics, and outcomes for this task. The survey years analyzed were 2014, which covers the period from 2011 to 2013; 2016, covering 2013 to 2015; 2018, covering 2015 to 2017; 2020, covering 2017 to 2019; and 2022, covering 2019 to 2021.

CPS data

The CPS data are used as part of the "denominator" for the displacement rates in the analysis. To align with the DWS survey years – 2014, 2016, 2018, 2020, and 2022 – we use monthly CPS data corresponding to the month and year of the DWS (i.e., basic monthly data from January 2014, 2016, 2018, 2020, and 2022).

ACS microdata

The ACS microdata are used to create Appalachian observations in the DWS and CPS data. The DWS and CPS data report limited geographic identifiers (state, metropolitan area, certain counties), so the ACS microdata, which are reported at the unit of Public Use Microdata Areas (PUMAs), are used to create weights for the Appalachian portion of the geographies identified in the DWS and CPS data.

The previous study used the 2000 Census 5 Percent Public Use Microdata Sample (PUMS). Given the timeframe of this study and the need to test socioeconomic, industry, and occupation variables, the project team initially tested several years of ACS microdata (all using 2010 PUMA geographies) to determine which year to use. The 2010 PUMA geographies were first used in 2012 ACS microdata, meaning that 5-year data could be used from 2016 (covering 2012-2016) through 2021 (covering 2017-2021). 2020 5-year data were excluded due to the use of experimental weights during the COVID-19 pandemic. (The 2022 5-year PUMS files were not available in time for inclusion in the analysis.[25])

9.3 Key Assumptions

This work made several assumptions:

- The Appalachian Region is defined by the 423 counties in the Appalachian Regional Commission's November 15, 2021 definition.[26] This definition is different from the one used by the previous study, as changes to the region have been made at various points since it was published.[27] It is worth noting that the eight independent cities in Virginia (Covington City, Galax City, Martinsville City, Radford City, Buena Vista City, Lexington City, Bristol City, and Norton City) are included in the analysis as part of the Appalachian Region.
- Following the approach of the previous study, any PUMA comprised partly or entirely of an Appalachian county was identified as an Appalachian Region PUMA.

9.4 Creating Appalachian Observations

Before analyzing the DWS data, it is necessary to identify the Appalachian observations in the underlying data. As discussed above, there are limited geographic identifiers in the data, so the geographies that are identified must be tagged as entirely within Appalachia ("in"), entirely outside of Appalachia ("out"), or partially within Appalachian ("partial"). (Example: Any observation in the state of West Virginia would be "in"; any observation in the state of Illinois would be "out"; and any observation in the nonmetro portion of Virginia would be "partial.") Though some observations have county identifiers, which provide certainty on whether the observation is in Appalachia, most observations only have metro/nonmetro identifiers. This means that the partial geographies consist of Metropolitan Statistical Areas (MSAs) and nonmetro portions of states.

25. https://www.census.gov/programs-surveys/acs/news/data-releases/2022/release.html#fiveyear.

26. https://www.arc.gov/appalachian-counties-served-by-arc/.

27. https://www.arc.gov/wp-content/uploads/2020/06/AppalachiaThenAndNowCompiledReports.pdf#page=6.

Identifying the Partial Geographies

Across the five survey years to be analyzed, CPS and DWS data are reported in two different MSA vintages. Data from April 2014 and earlier are reported in the June 2003 MSA definition, and data from May 2014 and later are reported in the February 2013 MSA definition.[28] This means that the 2014 DWS data are reported in the 2003 vintage, and the 2016, 2018, 2020, and 2022 DWS data are reported in the 2013 vintage. Since there are two sets of MSA vintages, there are two corresponding sets of partial geographies. Up to 60 partial geographies exist, but not all will be present in the CPS or DWS data.[29]

As noted by the previous study, there are several partial geographies that can be identified as "in" or "out" based on their state identifier. (That is, the unique state-MSA combination is entirely within or outside of the Appalachian Region.) In the 2003 vintage, there are three such combinations: the Pennsylvania county in the New York MSA; the West Virginia county in the Washington, DC MSA; and the West Virginia county in the Winchester, VA MSA. In the 2013 vintage, there are four such combinations: the two Tennessee counties in the Kingsport MSA; the Pennsylvania county in the New York MSA; the West Virginia county in the Washington, DC MSA; and the West Virginia county in the Winchester, VA MSA. However, it is worth noting that some of these partials do not exist in the CPS or DWS data. In addition, in the 2013 vintage, the entirety of nonmetro Pennsylvania is in Appalachia. In both years, of course, any observation in West Virginia is in Appalachia. As a result, these geographies are not considered partials. Each entry in the CPS and DWS data is tagged with its partial geography and status ("in", "out", or "partial").

28. https://cps.ipums.org/cps/codes/metfips_2014onward_codes.shtml#note.

29. It is worth noting that there is a transition period from May 2014 to July 2015, in which 38 MSAs continue to use the 2003 definition and the remainder switch to using the 2013 definition. After July 2015, all MSAs use the 2013 definition. This does not affect the DWS data, which are collected in January of the survey year (i.e., 2014, 2016, 2018, 2020, 2022), and it does not affect the use of the CPS data, which are also filtered to the month and year that match the DWS data. For more information, see: https://cps.ipums.org/cps/codes/metfips_2014onward_codes.shtml#note.

Table 29. Partial Geographies by Year of MSA Vintage

(2003 vintage used for 2014 DWS/CPS; 2013 vintage used for 2016, 2018, 2020, and 2022 DWS/CPS)

Type of Partial Geography	2003 MSA Definition	2013 MSA Definition
MSAs	Albany, NY Allentown, PA Athens, GA Atlanta, GA Bowling Green, KY Canton, OH Cincinnati, OH Greenville, SC Harrisburg, PA Lexington, KY Memphis, TN Montgomery, AL Nashville, TN New York, NY Roanoke, VA Tuscaloosa, AL Washington, DC Winchester, VA	Albany, NY Allentown, PA Athens, GA Atlanta, GA Bowling Green, KY Canton, OH Cincinnati, OH Columbus, OH Greenville, SC Harrisburg, PA Lexington, KY Memphis, TN Montgomery, AL Nashville, TN New York, NY Roanoke, VA Washington, DC Winchester, VA Winston-Salem, NC
Nonmetro Portions of States	Alabama Georgia Kentucky Maryland Mississippi New York North Carolina Ohio Pennsylvania South Carolina Tennessee Virginia	Alabama Georgia Kentucky Maryland Mississippi New York North Carolina Ohio South Carolina Tennessee Virginia

Creating a Crosswalk Between the PUMAs and the Partial Geographies

The 2010 PUMAs were crosswalked to the partial geographies using the 2010 equivalency files for the 13 Appalachian states. The equivalency files use four aggregation levels to show the relationship between the PUMAs and counties, minor civil divisions, places, and census tracts.30[30] Using the county aggregation level, the PUMAs are tagged if they contain (or are contained in) an Appalachian county. The counties are used to join the 2003 and 2013 MSA definitions and create a list of PUMAs comprising each partial geography.

Assessing Variables of Interest

As noted by the previous study, it is important to select fields that are consistent between CPS and ACS (or the Census). This involved a detailed review of all potential socioeconomic and industry/occupation-based variables available across all three datasets (CPS, DWS, and ACS IPUMS). Under consideration were a variety of measures to capture a wide range of demographic and socioeconomic characteristics (e.g., age, sex, marital status, race, ethnicity, nativity, language spoken, hours worked, migration, disability status, and veteran status). These variables needed to exist in both the ACS IPUMS and CPS/DWS data; needed to capture the same universe of respondents; and (where necessary) needed to be (re)coded so that the response categories were aligned with each other.

Socioeconomic variables under consideration were citizenship status, measures of physical or mental health conditions (difficulty with personal care, difficulty with eyesight, difficulty with hearing, difficulty with mobility outside of the home, difficulty with physical activities, and difficulty remembering), educational attainment, Hispanic ethnicity, marital status, race, sex, veteran status, year of immigration (if applicable), and age. All variables are categorical except for age.

Industry and occupation variables were initially rolled up to the major group level, providing 14 major industry groups and 11 major occupation groups. The major group was used instead of the detailed code in order to reduce dimensionality and the number of coefficients to be estimated. There are also slight changes to the industry and occupation definitions over time, starting with the codes introduced in January 2020, which affect the 2020 and 2022 DWS. The project team included an employment status interaction in the industry and occupation specification in order to account for the fact that the reported industry or occupation could refer to a previous, rather than the current, job.[31] It is also worth noting that the universe of respondents in the ACS data for industry and occupation fields is persons ages 16 or older whereas the universe in CPS is civilians ages 15 or older.

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30. https://usa.ipums.org/usa/volii/pumas10.shtml.

31. This is meant to differentiate the industry or occupation of people currently employed versus not (i.e., whether the reported industry or occupation refers to a current job versus a previous job). Reported industry/occupation for the currently employed reflects the current job. Reported industry/occupation for the not-currently-employed reflects the previous job, within the past 5 years.

It is worth noting that there are several additional categories of active duty military-related industries in addition to 9890 – Armed Forces that are included in the ACS IPUMS data but not in the CPS or DWS data (in 2016, this included 9670 – U.S. Army, 9680 – U.S. Air Force, 9690 – U.S. Navy, 9770 – U.S. Marines, 9780 – U.S. Coast Guard, 9790 – U.S. Armed Forces, Branch Not Specified, 9870 – Military Reserves or National Guard, and 9920 – Unemployed, last worked 5 years ago or earlier or never worked). In the ACS IPUMS data, these categories are coded as 0 and treated as if there was no industry data.

Similarly, there are several categories of active-duty military-related occupations in addition to 9840 – Armed Forces. These include: 9800 – Military Officer Special and Tactical Operations Leaders, 9810 – First-Line Enlisted Military Supervisors, 9820 – Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members, 9830 – Military, Rank Not Specified, and 9920 – Unemployed, with No Work Experience in the Last 5 Years or Earlier or Never Worked. In the ACS IPUMS data, these categories are also coded as 0 and treated as if there was no occupation data.

In re-specifying the model for analyzing the most recent years of DWS data, the intent was to consider more socioeconomic, and potentially more work-related, variables. In reviewing potential variables, the project team assessed the response fields and did re-codings to ensure they were consistent across the data sources. (A list of the variable re- codings is available upon request.)

Table 30. Variables Considered for Logit Model. Work-related variables are shaded gray.

Variable	Type	Description	Universe, ACS IPUMS	Universe, CPS
AGE	numeric	age	all persons	all persons
CITIZEN	factor	citizenship status (of foreign-born persons)	foreign-born persons	all respondents (appears to only be foreign-born)
CLASSWKRD	factor	class of worker (detailed)	persons age 16+ who had worked within the past 5 years	persons age 15+ who ever worked
DIFFCARE	factor	whether respondents have any physical or mental health condition that has lasted at least 6 months and makes it difficult for them to take care of their own personal needs, such as bathing, dressing, or getting around inside the home. Does not include temporary health conditions, such as broken bones or pregnancies	persons age 5+	civilians age 15+
DIFFEYE	factor	whether the respondent is blind or has serious difficulty seeing even with corrective lenses	all persons	civilians age 15+
DIFFHEAR	factor	whether the respondent is deaf or has serious difficulty hearing	all persons	civilians age 15+
DIFFMOB	factor	whether the respondent has any physical, mental, or emotional condition lasting six months or more that makes it difficult or impossible to perform basic activities outside the home alone. Does not include temporary health problems, such as broken bones	persons age 16+	civilians age 15+
DIFFPHYS	factor	whether the respondent has a condition that substantially limits one or more basic physical activities, such as walking, climbing stairs, reaching, lifting, or carrying	persons age 5+	civilians age 15+
DIFFREM	factor	whether the respondent has cognitive difficulties (such as learning, remembering, concentrating, or making decisions) because of a physical, mental, or emotional condition	persons age 5+	civilians age 15+
EDUC / EDUCD	factor	educational attainment (detailed)	all persons	persons age 14+ (in non-ASEC)
EMPSTATD	factor	employment status (detailed)	persons age 16+	persons age 15+
HISPAN	factor	Hispanic ethnicity	all persons	all persons
IND	factor	industry	persons age 16+ who had worked within the previous five years, not new workers	civilians age 15+ who: were currently employed; or had previously worked and were looking for work; or were not currently in the labor force but had worked in the preceding 12 months.
LABFORCE	factor	labor force status	persons age 16+	civilians age 15+
MARST	factor	marital status	persons age 15+	persons age 15+
OCC	factor	occupation	persons age 16+ who had worked within the previous five years, not new workers	civilians age 15+ who were employed, on layoff, unemployed but had worked in the past, or not in labor force but had worked in the past year
RACE	factor	race	all persons	all persons
SEX	factor	sex	all persons	all persons
VETSTAT	factor	veteran status	persons age 17+	civilians age 17+
YRIMMIG	numeric	year of immigration	foreign-born persons and persons born in U.S. outlying areas	foreign-born persons and persons born in U.S. outlying areas

In addition to these variables, the project team also considered ACS variables such as nativity, ability to speak English, year of naturalization, years in the U.S., weeks worked last year, occupation by SOC code, industry by NAICS code, 1-year migration status, and difficulties with/disabilities in blindness, deafness, or severe vision or hearing impairments, but these variables were not available in CPS.

Specifying Logit Models to Determine the Partial Geography's Appalachian Share

Logit models predict outcomes (e.g., mode choice) rather than continuous dependent variables (e.g., household income, poverty rate). Logit models reflect "log-odds" between two different outcomes and take the following form:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_i X + \varepsilon \rightarrow \frac{p}{1-p} = e^{\beta_0 + \beta_i X + \varepsilon}$$

There are several steps involved in the logit model specification.

1. *Determining Which Year of ACS Microdata to Use*

First, the project team assessed which year of ACS microdata to use. As discussed above, the microdata are reported in 2010 PUMAs, which first appear in 2012. In order to maximize sample size and acquire the necessary socioeconomic, industry, and occupation variables for testing different models, the project team decided to use 5-year data. Thus, the project team considered using data from 2016 (capturing the 2012 to 2016 period), 2017 (capturing the 2013 to 2017 period), 2018 (capturing the 2014 to 2018 period), 2019 (capturing the 2015 to 2019 period), and 2021 (capturing the 2016 to 2021 period). The project team intentionally excluded 2020 data due to its use of experimental weights and to avoid any confounding effects from data collection during the COVID-19 pandemic.[32]

The project team ran five logit models using the specification established by the previous study (age, sex, marital status, race, and education) to model the probability of a PUMA in a partial geography in any of the thirteen states being located in Appalachia. The model results were not dramatically different in terms of the Akaike Information Criterion (AIC), though the AIC was lowest in the model specified with 2016 data. (See Table 31.) All variables were significant in all years, except for one of the education factors (12th grade, no high school diploma) in the model specified with 2021 data. As a result, the project team decided to use 2016 5-year data for the logit model specification. Another reason to use the 2016 data is that it marks the midpoint in the years covered by the DWS data to be analyzed (2011 to 2021).

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32. https://www.census.gov/programs-surveys/acs/technical-documentation/user-notes/2022-06.html.

Table 31. AIC for Different Years of ACS Microdata

Year of ACS Microdata (5-year)	Model AIC Under Previous Study's Specifications
2016	70,960,363
2017	71,231,871
2018	71,394,184
2019	71,619,876
2021	72,428,863

2. *Specifying the Model*

Second, after determining which year of ACS microdata to use, the project team specified several different types of models to determine which specifications offered the best predictive power for the partial geographies. The team specified the previous study's model, one with a mix of socioeconomic variables (including ones used by the previous study), one with industry and occupation variables interacted with labor force, and one using a combination of socioeconomic, industry and occupation variables.

Since these variables are primarily categorical, it is not possible to create a standard correlation matrix. Instead, we use two-way contingency tables to describe the (pairwise) relationship between two categorical variables and test their independence using the chi-square test of independence. Excluding age, there are 19 factor/categorical socioeconomic and industry/occupation-based variables under consideration, which means there are 171 pairwise chi-squared tests of independence.[33] None of the pairwise tests indicate variable dependence when assessed for the ACS PUMA data in the partial geographies. The model AIC for different specifications is shown in Table 32, and these models predict the probability of any PUMA in the 13 Appalachian states being in the Appalachian Region proper.

33. We arrive at 171 pairwise test via the following math: 19!/(17!*2!) =(19*18)/2 = 171.

Table 32. Summary of Results by Model Specification (Sorted by Lowest Model AIC) – for all PUMAs in the 13 states

Model Specification	Model AIC
Combination – Socioeconomic + Industry/Occupation*Employment Status Plus COW, LF ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + DiffPhys + DiffRem + Education + Hispanic + Sex * Marital Status + Race + Veteran Status + Year of Immigration + Class of Worker + Labor Force + Industry * Employment Status + Occupation * Employment Status)	113,967,752
Combination – Socioeconomic + Industry/Occupation * Employment Status ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + DiffPhys + DiffRem + Education + Hispanic + Sex * Marital Status + Race + Veteran Status + Year of Immigration + Industry * Employment Status + Occupation * Employment Status)	114,019,741
Combination – Socioeconomic + Industry/Occupation ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + DiffPhys + DiffRem + Education + Hispanic + Marital Status * Sex + Race + Veteran Status + Year of Immigration + Industry + Occupation)	114,178,055
Socioeconomic Variables with Sex * Marital Status Interaction ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + DiffPhys + DiffRem + Education + Hispanic + Marital Status * Sex + Race + Veteran Status + Year of Immigration)	114,696,383
Socioeconomic Variables ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + DiffPhys + DiffRem + Education + Hispanic + Marital Status + Race + Sex + Veteran Status + Year of Immigration)	114,697,861
Previous Study ARC = f(Age + Sex*Marital Status + Race + Education)	116,370,900
Industry/Occupation * Employment Status Plus COW, LF ARC = f(Class of Worker + Labor Force + Industry * Employment Status + Occupation * Employment Status)	120,101,899
Industry/Occupation * Employment Status ARC = f(Industry * Employment Status + Occupation * Employment Status)	120,176,842
Industry/Occupation ARC = f(Industry + Occupation)	120,464,009

The models were run a second time (along with several new specifications) to predict the probability of a PUMA in a partial geography in the 13 Appalachian states being in the Appalachian Region. (AICs are shown in Table 33.) The reason for using only the PUMAs in the partials is to eliminate PUMAs in geographies that are entirely within the Appalachian Region (e.g., the entire state of West Virginia, where every PUMA is in the Appalachian Region), and focus on PUMAs in the contested partial geographies. This has the added benefit of significantly reducing the file size and makes the models run much faster.

Table 33. Summary of Results by Model Specification (Sorted by Lowest Model AIC) – only for PUMAs in a partial

	Count, Observations Outside Partial Geographies in the 13 ARC States	Count, Observations Within Partial Geographies in the 13 ARC States	%, Observations Outside Partial Geographies in the 13 ARC States	%, Observations Within Partial Geographies in the 13 ARC States
Industry Sector				
0/Not Available	2,016,976	120,344	41%	45%
Agriculture, Forestry, Fishing, and Hunting	29,114	3,590	1%	1%
Mining	10,401	899	0%	0%
Transportation and Utilities	137,823	7,445	3%	3%
Construction	167,008	10,118	3%	4%
Manufacturing	295,557	23,445	6%	9%
Wholesale and Retail Trade	391,428	20,873	8%	8%
Information	57,153	1,896	1%	1%
Financial Activities	171,061	6,222	3%	2%
Professional and Business Services	309,100	10,922	6%	4%
Educational and Health Services	687,548	34,302	14%	13%
Leisure and Hospitality	270,249	12,797	6%	5%
Other Services	141,788	7,030	3%	3%
Public Administration	152,860	7,507	3%	3%
Military*	54,659	2,087	1%	1%
Occupation Sector				
0/Not Available	2,016,976	120,344	41%	45%
Management, business, and financial occupations	397,787	15,922	8%	6%
Professional and related occupations	638,382	26,715	13%	10%
Service occupations	513,595	27,296	10%	10%
Sales and related occupations	297,892	14,231	6%	5%
Office and administrative support functions	388,162	19,667	8%	7%
Farming, fishing, and forestry occupations	14,426	1,567	0%	1%
Construction and extraction occupations	134,932	8,568	3%	3%
Installation, maintenance, and repair occupations	87,899	5,774	2%	2%
Production occupations	175,452	15,433	4%	6%
Transportation and material moving occupations	183,372	11,994	4%	4%
Military-specific*	43,850	1,966	1%	1%
Total	**4,892,725**	**269,477**	**100%**	**100%**

After determining the best model specification, it was rerun on all years of ACS microdata (2016, 2017, 2018, 2019, and 2021) to confirm that 2016 still held the best results, which it did.

3. *Adapting and Running the Model for the Partial Geographies*

However, some of the coefficients (particularly the employment status interaction term) were not able to be specified due to small sample sizes, as well as extreme values for certain coefficients. The final model specification used for the partial geographies is a variation of the second-best model, minus the industry and occupation variables:

$$ARC = f(Age + Citizen + DiffCare + DiffEye + DiffHear + DiffMob + Education \\ + Hispanic + Sex * Marital\,Status + Race + Veteran\,Status \\ + Year\,of\,Immigration + Class\,of\,Worker + Labor\,Force)$$

4. *Running the Model on All Partial Geographies*

Then, the project team ran the logit model for each partial geography, recording the model output and coefficients. The coefficients were saved into a common data frame to be joined back to the DWS and CPS data for calculating Appalachian Region weights. There are some interaction terms that are unable to be defined for all geographies.

Qualifiers and Caveats

There are several qualifiers and caveats to note. The quality of the estimates (and model) depends on the number of observations in each partial, and there is at least one partial (Bowling Green, KY, 2003) with questionable results from the model.

Second, though it was the intention of the project team to build out deeper industry/occupation analysis, small numbers of observations prevented this from working as planned. After rolling the detailed industry and occupation codes to sector approximations, more than 40% of observations for 2016 are missing industry data, and there is wide variation among represented industries. (See Table 34.) Attempts to further disaggregate the data by industry or occupation sector show wide variation in data availability. It is worth noting that industry sector information can be missing for at least several reasons (observations for people not in the labor force, as well as unavailable due to N/A's).

Table 34. Percent of Observations for PUMAs Outside and Inside of Partials by Industry and Occupation Sector, 2016 ACS Microdata

	Count, Observations Outside Partial Geographies in the 13 ARC States	Count, Observations Within Partial Geographies in the 13 ARC States	%, Observations Outside Partial Geographies in the 13 ARC States	%, Observations Within Partial Geographies in the 13 ARC States
Industry Sector				
0/Not Available	2,016,976	120,344	41%	45%
Agriculture, Forestry, Fishing, and Hunting	29,114	3,590	1%	1%
Mining	10,401	899	0%	0%
Transportation and Utilities	137,823	7,445	3%	3%
Construction	167,008	10,118	3%	4%
Manufacturing	295,557	23,445	6%	9%
Wholesale and Retail Trade	391,428	20,873	8%	8%
Information	57,153	1,896	1%	1%
Financial Activities	171,061	6,222	3%	2%
Professional and Business Services	309,100	10,922	6%	4%
Educational and Health Services	687,548	34,302	14%	13%
Leisure and Hospitality	270,249	12,797	6%	5%
Other Services	141,788	7,030	3%	3%
Public Administration	152,860	7,507	3%	3%
Military*	54,659	2,087	1%	1%
Occupation Sector				
0/Not Available	2,016,976	120,344	41%	45%
Management, business, and financial occupations	397,787	15,922	8%	6%
Professional and related occupations	638,382	26,715	13%	10%
Service occupations	513,595	27,296	10%	10%
Sales and related occupations	297,892	14,231	6%	5%
Office and administrative support functions	388,162	19,667	8%	7%
Farming, fishing, and forestry occupations	14,426	1,567	0%	1%
Construction and extraction occupations	134,932	8,568	3%	3%
Installation, maintenance, and repair occupations	87,899	5,774	2%	2%
Production occupations	175,452	15,433	4%	6%
Transportation and material moving occupations	183,372	11,994	4%	4%
Military-specific*	43,850	1,966	1%	1%
Total	**4,892,725**	**269,477**	**100%**	**100%**

*Missing in CPS documentation definition. Note: Generally, 0/NA's refer to people that are: "less than 16 years old/ unemployed who never worked/NILF (not in labor force) who last worked more than 5 years ago."[34] Source: ACS IPUMS; Mass Economics analysis.

34. See: https://usa.ipums.org/usa/volii/ind2013.shtml; https://usa.ipums.org/usa/volii/occ_acs.shtml.

Calculating Simple Labor Force Share to Determine the Partial Geography's Appalachian Share

The labor force share estimates the Appalachian share in the partial geographies using the constituent PUMAs and controls for any partial PUMAs with the equivalency file's population share in 2010, following the approach of the previous study.

From the PUMA-partial geography crosswalk, it is possible to calculate the share of Appalachian Region population in each PUMA-partial geography. Then, we apply this share to the ACS labor force share to estimate the share of Appalachian Region labor force in each PUMA-partial geography.

Applying the Weights to DWS and CPS

The project team then created Appalachian observations in the DWS and CPS data. Any observations in the CPS or DWS data corresponding to a partial geography are duplicated: one corresponds to the Appalachian observation, with a weight of p, and the other corresponds to the non-Appalachian observation, with a weight of $(1 - p)$. Logistic weights and simple labor force share weights were used.

The logistic weight $w_{lg,\alpha}$ for partial geography α is calculated as:

$$w_{lg,\alpha} = p_\alpha = \frac{\left(\frac{p_\alpha}{1 - p_\alpha}\right)}{1 + \left(\frac{p_\alpha}{1 - p_\alpha}\right)} = \frac{e^{\beta_{0,\alpha} + \beta_{i,\alpha} X_\alpha}}{1 + e^{\beta_{0,\alpha} + \beta_{i,\alpha} X_\alpha}}$$

The labor force weight $w_{lf,\alpha}$ for partial geography α comprised of N PUMAs is calculated as:

$$w_{lf,\alpha} = \frac{\sum_{i=1}^{N} LaborForce_i * \frac{TotPop_{i,\,ARC}}{TotPop_i}}{\sum_{i=1}^{N} LaborForce_i}$$

These weights are applied to the CPS and DWS observations (rows) as shown in Table 35.

Table 35. Applying Weights to Observations

Type of Observation	Appalachian Region Identifier	DWS	CPS
"in"	1	100% * DWSUPPWT	100% * WTFINL
"out"	0	100% * DWSUPPWT	100% * WTFINL
"partial"	1	w * DWSUPPWT	w * WTFINL
	0	(1-w) * DWSUPPWT	(1-w) * WTFINL

A summary of the weights for the partial geographies is shown in Table 36 and Table 37.

Table 36. Weights Summary for 2003 Vintage of Partial Geographies

Name (2003 Definition)	Logistic Weight (Unwtd.)	Labor Force Share Weight (Unwtd.)	Labor Force Share Weight (ACS Counties), 2021 5-yr
Albany-Schenectady-Troy, NY	12%	11%	3%
Allentown-Bethlehem-Easton, PA-NJ	20%	9%	7%
Athens-Clarke County, GA	57%	17%	13%
Atlanta-Sandy Springs-Marietta, GA	43%	39%	35%
Bowling Green, KY	54%	55%	7%
Canton-Massillon, OH	33%	7%	7%
Cincinnati-Middletown, OH-KY-IN	18%	11%	11%
Harrisburg-Carlisle, PA	27%	8%	8%
Lexington-Fayette, KY	43%	6%	7%
Memphis, TN-MS-AR	20%	9%	2%
Montgomery, AL	54%	21%	20%
Nashville-Davidson--Murfreesboro, TN	7%	5%	3%
New York-Northern New Jersey-Long Island, NY-NJ-PA	2%	1%	0%
Roanoke, VA	66%	13%	12%
Tuscaloosa, AL	100%	88%	97%
Washington-Arlington-Alexandria, DC-VA-MD-WV	4%	4%	1%
Nonmetro Alabama	67%	55%	51%
Nonmetro Georgia	37%	32%	28%
Nonmetro Kentucky	59%	42%	54%
Nonmetro Maryland	17%	14%	9%
Nonmetro Mississippi	47%	32%	38%
Nonmetro New York	39%	37%	38%
Nonmetro North Carolina	30%	26%	23%
Nonmetro Ohio	50%	45%	45%
Nonmetro Pennsylvania	89%	89%	86%
Nonmetro South Carolina	25%	21%	14%
Nonmetro Tennessee	70%	65%	58%
Nonmetro Virginia	53%	43%	40%

Table 37. Weights Summary for 2013 Vintage of Partial Geographies

Name (2013 Definition)	Logistic Weight (Unwtd.)	Labor Force Share Weight (Unwtd.)	Labor Force Share Weight (ACS Counties), 2021 5-yr
Albany–Schenectady–Troy, NY	11%	11%	3%
Allentown–Bethlehem–Easton, PA–NJ	20%	9%	7%
Athens–Clarke County, GA	53%	17%	13%
Atlanta–Sandy Springs–Marietta, GA	40%	39%	35%
Bowling Green, KY	57%	15%	6%
Canton–Massillon, OH	32%	7%	7%
Cincinnati–Middletown, OH–KY–IN	18%	11%	11%
Columbus, OH	10%	9%	3%
Greenville–Anderson–Mauldin, SC	100%	92%	93%
Harrisburg–Carlisle, PA	26%	8%	8%
Lexington–Fayette, KY	44%	6%	7%
Memphis, TN–MS–AR	18%	9%	3%
Montgomery, AL	48%	21%	20%
Nashville–Davidson––Murfreesboro, TN	6%	5%	3%
New York–Northern New Jersey–Long Island, NY–NJ–PA	2%	1%	0%
Roanoke, VA	62%	13%	12%
Washington–Arlington–Alexandria, DC–VA–MD–WV	4%	4%	1%
Winchester, VA–WV	60%	64%	15%
Winston–Salem, NC	77%	79%	75%
Nonmetro Alabama	72%	59%	60%
Nonmetro Georgia	38%	36%	29%
Nonmetro Kentucky	59%	43%	53%
Nonmetro Maryland	36%	35%	19%
Nonmetro Mississippi	49%	34%	38%
Nonmetro New York	41%	40%	41%
Nonmetro North Carolina	37%	34%	31%
Nonmetro Ohio	48%	43%	41%
Nonmetro South Carolina	27%	26%	17%
Nonmetro Tennessee	63%	59%	59%
Nonmetro Virginia	45%	37%	40%

9.5 Analyzing the DWS

Universe of Displaced Workers

The universe of displaced workers consists of those who: lost their job at some point during the last three years due to one of the three types of displacement events (Type 1, plant or company closed down or moved; Type 2, plant or company operating but lost/left job because of insufficient work; and Type 3, plant or company operating but lost/left job because position or shift was abolished); were long-tenured, meaning they had worked at the job from which they were displaced for at least three years; and do not expect to be recalled in the next six months.

Displacement Rates

Following the approach of the previous study, we calculate the displacement rate for any survey year as:

$$Displacement\ Rate_y = \frac{disp_y}{disp.notemp_y + tot.emp_y}$$

Diverging from the previous study, we calculate the overall displacement rate (i.e., for the 2011-2021 time period) as a weighted average of the displacement rates from the individual surveys.

Where:

- *disp* := number of workers reporting displacement at any time over the previous three years
- *disp.notemp* := number of workers reporting displacement at any time over the previous three years that are not currently employed
- *tot.emp* := total employment as of the survey month and year For y = 2014, 2016, 2018, 2020, and 2022

Significance Testing

"Significant findings" are significant at the 90% level.

The project team referenced various BLS documentation and emailed specific questions to the Census Source and Accuracy Department to refine the approach for significance testing estimates from the DWS. The team used the Generalized Variance Function (GVF) approach with the information in the Source and Accuracy section (attachment 16) in each year of CPS documentation. This method approximates the standard errors for different types of measures. The team used the alpha and beta parameters shown in Table 38.

Table 38. Parameters Used for Significance Testing

Survey Year	Alpha, DWS	Beta, DWS	Alpha, CPS	Beta, CPS	Notes
2014	-0.000016	3,068	-0.000016	3,068	
2016	-0.000013	2,481	-0.000013	2,481	
2018	-0.000013	2,481	-0.000013	2,481	
2020	-0.000017	4,127	-0.000013	2,481	CPS parameters from Table 7; DWS parameters from Table 8 (uses long-tenured)
2022	-0.000024	5,842	-0.000013	2,481	CPS parameters from Table 7; DWS parameters from Table 8 (uses long-tenured)
2011-2022*	-0.000024	5,842	-0.000013	2,481	CPS parameters from Table 7; DWS parameters from Table 8 (uses long-tenured)

*2011-2022 is estimated using 2022 alpha and beta parameters.

These parameters are used to calculate standard errors for the numerator of the displacement rate (number of displaced workers) and for each component of the denominator (number of displaced workers not currently employed uses the DWS parameters; total employment uses the CPS parameters). The equation used to calculate the standard errors for the numerator and each component of the denominator is:

$$SE = \sqrt{\alpha x^2 + \beta x}$$

The standard error for the denominator is calculated as the square root of the sum of the squares of each component.

Following the guidance from the ASEC Source and Accuracy documentation,[35] the standard error of the displacement rate, as an estimated ratio of x/y, is calculated as:

$$SE_{\frac{x}{y}} = \frac{x}{y}\sqrt{\left(\frac{SE_x}{x}\right)^2 + \left(\frac{SE_y}{y}\right)^2}$$

35. Note that the formula also includes a subtracted term multiplied by the correlation rate between the two variables, but we do not have a correlation rate and thus exclude the term, which makes our estimate conservative. See: https://www2.census.gov/programs- surveys/cps/techdocs/cpsmar23.pdf#page=367.

Finally, following Census significance testing procedures,[36] we use a simple Z test to compare whether two values (including rates) are significantly different:

$$Z = \frac{R_1 - R_2}{\sqrt{SE_1^2 + SE_2^2}}$$

Two estimates are considered significantly different at the 90% level if the absolute value of Z > 1.645.

It is important to note that this is an adaptation of BLS significance testing procedures, and, as noted in the previous study, is approximate at best, though it provides a consistent method for significance testing. It is also worth noting that we used topline parameters, not parameters specific to certain populations (e.g., sex, race) since they were not available for all the demographic groups analyzed. While the previous study does not provide many details on their approach to significance testing, we believe this is reasonably consistent with their process. Replicate weights[37] might be a more robust and preferred approach to significance testing, but there are some computational drawbacks for our circumstances due to the fact we are estimating coefficients for 50+ partial geographies, as well as using these coefficients to apportion weighted observations in the data. In the future, we may revisit the approach for significance testing, particularly when it comes to assessing the significance of changes over time.

Sample Sizes

Small sample sizes are a concern for interpreting the findings. While BLS has their own standards for reporting out estimates and generally won't publish data where the "base is less than 75,000,"[38] it is important to consider the sample size count for reporting out displacement statistics as it pertains to the numerator (i.e., the number of observations contributing to the overall estimate of the displaced) as well as the number of observations contributing to the denominator, particularly the number of observations capturing displaced workers that are not currently employed. We are currently only reporting values with a sample size of at least 5 observations for the numerator; that is, any estimates where there are fewer than 5 observations for displaced workers are not reported. We did not impose any restrictions on the sample size for the displaced not currently employed observations because this represents a comparatively small share of the denominator.

36 . https://www2.census.gov/programs-surveys/acs/tech_docs/statistical_testing/2020_Instructions_for_Stat_Testing_ACS.pdf.

37. Replicate weights are thought to offer better ("more precise") confidence intervals for estimates derived from survey data by providing 160 different weights for person-level data. The standard error is recalculated using a formula that takes into account results using each replicate weight, as well as the results from the full-sample weight. See: https://cps.ipums.org/cps/repwt.shtml#q10.

38. See, e.g., https://www.bls.gov/news.release/archives/uisup_03292023.htm.

Comparing the Data

Finally, the previous study compared demographic characteristics of the DWS samples. Table 39 shows these characteristics for the 2016 data, and these summaries indicate that the logistic and labor force share weights are relatively closely aligned with the microdata approximation.

Table 39. Summary of Demographic Characteristics, 2016

			APPALACHIAN REGION		
Variable	**Group**	**U.S., DWS Sample, 2016**	**Logistic Weight, DWS Sample, 2016**	**Labor Force Share, DWS Sample, 2016**	**PUMA Approximation, ACS 5-Year Microdata, 2016**
Race	White, non-Hispanic	66%	82%	80%	84%
	Black or African American, non-Hispanic	12%	11%	13%	10%
	Other Race, non-Hispanic	8%	3%	3%	3%
	Hispanic	15%	4%	4%	4%
Sex	Male	48%	48%	48%	48%
	Female	52%	52%	52%	52%
Age	20-34	28%	26%	26%	25%
	35-54	35%	34%	34%	35%
	55+	37%	40%	40%	40%
Educational Attainment	Less than HS	11%	13%	12%	14%
	High School Diploma/GED	29%	35%	35%	35%
	Some College or Associate's	29%	27%	27%	29%
	Bachelor's Degree	21%	16%	17%	14%
	Graduate / Post-Graduate Degree	12%	9%	9%	8%
Marital Status	Married	55%	57%	56%	54%
	Not Married	45%	43%	44%	46%

Source: CPS DWS; ACS IPUMS; Mass Economics analysis.

9.6 Supplemental Figures

Table 40. Industries with High Displacement Rates Nationally, 2011-2013

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Jobs, U.S.	Number of Displaced Workers, U.S.
1	Farm Supplies Merchant Wholesalers	20%	32,000	7,000
2	Water Transportation	17%	52,800	10,000
3	Coal Mining	17%	79,500	15,900
4	Office Supplies and Stationery Stores	16%	132,000	21,300
5	Ship and Boat Building	15%	138,200	22,000
6	Cut and Sew, and Apparel Accessories and Other Apparel Manufacturing	13%	219,700	31,300
7	Leather and Hide Tanning and Finishing, and Other Leather and Allied Product Manufacturing	12%	17,900	2,600
8	Other Information Services, Except Libraries and Archives, and Internet Publishing And Broadcasting and Web Search Portals	12%	30,500	3,700
9	Household Appliance Manufacturing	12%	56,000	7,100
10	Alcoholic Beverages Merchant Wholesalers	11%	114,300	13,000

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis

Table 41. Industries with High Displacement Rates Nationally, 2013-2015

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Jobs, U.S.	Number of Displaced Workers, U.S.
1	Clay Building Material and Refractories Manufacturing	30%	23,400	7,100
2	Miscellaneous Petroleum and Coal Products	23%	6,000	1,400
3	Leather and Hide Tanning and Finishing, and Other Leather and Allied Product Manufacturing	23%	17,200	5,000
4	Other Information Services, Except Libraries and Archives, and Internet Publishing and Broadcasting and Web Search Portals	20%	33,300	6,700
5	Aerospace Products and Parts Manufacturing	16%	61,000	9,900
6	Coal Mining	16%	66,700	12,100
7	Metal Ore Mining	14%	29,400	4,500
8	Tobacco Manufacturing	14%	22,000	3,700
9	Apparel, Piece Goods, and Notions Merchant Wholesalers	14%	96,700	13,300
10	Wholesale Electronic Markets and Agents and Brokers	13%	83,500	11,300

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis

Table 42. Industries with High Displacement Rates Nationally, 2015-2017

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Jobs, U.S.	Number of Displaced Workers, U.S.
1	Coal Mining	25%	48,500	13,100
2	Sewing, Needlework, and Piece Goods Stores	23%	24,800	6,300
3	Metals and Minerals, Except Petroleum, Merchant Wholesalers	19%	35,300	7,400
4	Scenic and Sightseeing Transportation	19%	27,200	5,100
5	Construction, and Mining and Oil and Gas Field Machinery Manufacturing	17%	141,500	25,100
6	Farm Supplies Merchant Wholesalers	17%	43,100	7,200
7	Shoe Stores	16%	80,900	15,100
8	Support Activities For Mining	16%	438,200	77,400
9	Knitting Fabric Mills, and Apparel Knitting Mills	16%	22,800	3,700
10	Engine, Turbine, and Power Transmission Equipment Manufacturing	15%	36,900	6,700

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis

Table 43. Industries with High Displacement Rates Nationally, 2017-2019

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Jobs, U.S.	Number of Displaced Workers, U.S.
1	Coating, Engraving, Heat Treating, and Allied Activities	23%	82,800	22,900
2	Book Stores and News Dealers	22%	90,700	21,400
3	Other Information Services, Except Libraries and Archives, and Internet Publishing and Broadcasting and Web Search Portals	20%	25,100	5,000
4	Software Publishers	15%	42,700	6,800
5	Other Direct Selling Establishments	13%	144,800	18,600
6	Nonferrous Metal (Except Aluminum) Production and Processing	12%	41,600	5,400
7	Sound Recording Industries	11%	35,400	4,400
8	Textile Product Mills, Except Carpet and Rug	11%	55,400	6,100
9	Animal Food, Grain and Oilseed Milling	10%	139,400	15,300
10	Oil and Gas Extraction	10%	131,500	13,700

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis

Table 44. Industries with High Displacement Rates Nationally, 2019-2021

Rank, Displacement Rate, U.S.	Census Industry	Displacement Rate, U.S.	Jobs, U.S.	Number of Displaced Workers, U.S.
1	Knitting Fabric Mills, and Apparel Knitting Mills	55%	8,600	4,700
2	Railroad Rolling Stock Manufacturing	34%	19,800	6,700
3	Oil and Gas Extraction	22%	60,200	15,900
4	Other Consumer Goods Rental	20%	77,000	15,300
5	Engine, Turbine, and Power Transmission Equipment Manufacturing	19%	32,000	7,300
6	Clay Building Material and Refractories Manufacturing	16%	15,200	2,800
7	Miscellaneous Nonmetallic Mineral Product Manufacturing	13%	35,100	5,200
8	Scenic and Sightseeing Transportation	13%	26,500	3,500
9	Petroleum Refining	12%	194,900	27,800
10	Shoe Stores	12%	72,800	9,100

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis

Out of 38 unique Census industries in the top ten in the 2011-2013, 2013-2015, 2015-2017, 2017-2019, or 2019- 2021 time periods, only two Census industries made the top ten in three time periods: Coal Mining and Other Information Services (shaded in dark green in Table 45). An additional eight Census industries made the top ten in two time periods (shaded in light green).

Table 45. Census Industries with Top 10 Displacement Rates Nationally, 2011-2021

Census Industry	Rank 2011-2013	Rank 2013-2015	Rank 2015-2017	Rank 2017-2019	Rank 2019-2021
Farm Supplies Merchant Wholesalers	1	NA	6	NA	NA
Water Transportation	2	NA	NA	NA	NA
Coal Mining	3	6	1	NA	NA
Office Supplies and Stationery Stores	4	NA	NA	NA	NA
Ship and Boat Building	5	NA	NA	NA	NA
Cut and Sew, and Apparel Accessories and Other Apparel Manufacturing	6	NA	NA	NA	NA
Leather + Hide Tanning + Finishing, + Other Leather + Allied Product Mfg.	7	3	NA	NA	NA
Other Information Services, E.G. Libraries, Archives, and Internet Publishing, Broadcasting, and Web Search Portals	8	4	NA	3	NA
Household Appliance Manufacturing	9	NA	NA	NA	NA
Alcoholic Beverages Merchant Wholesalers	10	NA	NA	NA	NA
Clay Building Material and Refractories Manufacturing	NA	1	NA	NA	6
Miscellaneous Petroleum and Coal Products	NA	2	NA	NA	NA
Aerospace Products and Parts Manufacturing	NA	5	NA	NA	NA
Metal Ore Mining	NA	7	NA	NA	NA
Tobacco Manufacturing	NA	8	NA	NA	NA
Apparel, Piece Goods, and Notions Merchant Wholesalers	NA	9	NA	NA	NA
Wholesale Electronic Markets and Agents and Brokers	NA	10	NA	NA	NA
Sewing, Needlework, and Piece Goods Stores	NA	NA	2	NA	NA
Metals and Minerals, Except Petroleum, Merchant Wholesalers	NA	NA	3	NA	NA
Scenic and Sightseeing Transportation	NA	NA	4	NA	8
Construction, Mining, Oil, and Gas Field Machinery Manufacturing	NA	NA	5	NA	NA
Shoe Stores	NA	NA	7	NA	10
Support Activities For Mining	NA	NA	8	NA	NA
Knitting Fabric Mills, and Apparel Knitting Mills	NA	NA	9	NA	1
Engine, Turbine, and Power Transmission Equipment Manufacturing	NA	NA	10	NA	5
Coating, Engraving, Heat Treating, and Allied Activities	NA	NA	NA	1	NA
Book Stores and News Dealers	NA	NA	NA	2	NA
Software Publishers	NA	NA	NA	4	NA
Other Direct Selling Establishments	NA	NA	NA	5	NA
Nonferrous Metal (Except Aluminum) Production and Processing	NA	NA	NA	6	NA
Sound Recording Industries	NA	NA	NA	7	NA
Textile Product Mills, Except Carpet and Rug	NA	NA	NA	8	NA
Animal Food, Grain and Oilseed Milling	NA	NA	NA	9	NA
Oil and Gas Extraction	NA	NA	NA	10	3
Railroad Rolling Stock Manufacturing	NA	NA	NA	NA	2
Other Consumer Goods Rental	NA	NA	NA	NA	4
Miscellaneous Nonmetallic Mineral Product Manufacturing	NA	NA	NA	NA	7
Petroleum Refining	NA	NA	NA	NA	9

Source: CPS DWS; Mass Economics analysis.

Table 46. Industries Displacing the Most Workers, 2011-2013

Rank, Number of Displaced Workers, U.S.	Census Industry	Number of Displaced Workers, U.S.	Jobs, U.S.	Displacement Rate
1	Construction	409,700	9,081,800	4%
2	Restaurants and Other Food Services	200,100	6,853,000	3%
3	General Medical and Surgical Hospitals, and Specialty (Except Psychiatric and Substance Abuse) Hospitals	127,100	6,620,300	2%
4	Elementary and Secondary Schools	124,200	9,106,300	1%
5	Computer Systems Design and Related Services	101,000	2,222,400	4%
6	Insurance Carriers	91,000	2,792,300	3%
7	Architectural, Engineering, and Related Services	81,300	1,389,200	6%
8	Supermarkets and Other Grocery (Except Convenience) Stores	72,200	2,386,600	3%
9	Banking and Related Activities	68,000	2,096,300	3%
10	Colleges, Universities, and Professional Schools, Including Junior Colleges	66,700	3,504,100	2%

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

Table 47. Industries Displacing the Most Workers, 2013-2015

Rank, Number of Displaced Workers, U.S.	Census Industry	Number of Displaced Workers, U.S.	Jobs, U.S.	Displacement Rate
1	Construction	216,800	9,688,400	2%
2	Restaurants and Other Food Services	141,700	7,531,200	2%
3	Elementary and Secondary Schools	99,300	9,290,000	1%
4	Computer Systems Design and Related Services	96,900	2,673,300	4%
5	General Medical and Surgical Hospitals, and Specialty (Except Psychiatric And Substance Abuse) Hospitals	85,800	6,741,100	1%
6	Banking and Related Activities	83,400	2,138,700	4%
7	Lessors Of Real Estate, and Offices Of Real Estate Agents and Brokers	72,200	2,519,300	3%
8	Support Activities For Mining	55,600	577,900	9%
9	Supermarkets and Other Grocery (Except Convenience) Stores	53,700	2,431,800	2%
10	Insurance Carriers	52,400	2,895,700	2%

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

Table 48. Industries Displacing the Most Workers, 2015-2017

Rank, Number of Displaced Workers, U.S.	Census Industry	Number of Displaced Workers, U.S.	Jobs, U.S.	Displacement Rate
1	Construction	164,800	10,838,000	2%
2	Restaurants and Other Food Services	146,700	7,022,800	2%
3	Computer Systems Design and Related Services	108,700	3,359,300	3%
4	Architectural, Engineering, and Related Services	94,100	1,698,600	5%
5	Insurance Carriers	79,500	2,836,400	3%
6	Colleges, Universities, and Professional Schools, Including Junior Colleges	79,000	3,707,700	2%
7	Support Activities For Mining	77,400	438,200	16%
8	General Medical and Surgical Hospitals, and Specialty (Except Psychiatric and Substance Abuse) Hospitals	65,500	6,912,000	1%
9	Elementary and Secondary Schools	60,000	9,238,500	1%
10	Department Stores	47,500	1,911,900	2%

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

Table 49. Industries Displacing the Most Workers, 2017-2019

Rank, Number of Displaced Workers, U.S.	Census Industry	Number of Displaced Workers, U.S.	Jobs, U.S.	Displacement Rate
1	Construction	192,600	10,819,700	2%
2	Computer Systems Design and Related Services	118,400	3,937,100	3%
3	Restaurants and Other Food Services	88,000	7,633,700	1%
4	Agencies, Brokerages, and Other Insurance Related Activities	70,700	866,200	8%
5	Elementary and Secondary Schools	57,900	9,589,100	1%
6	General Medical and Surgical Hospitals, and Specialty (Except Psychiatric and Substance Abuse) Hospitals	53,200	7,378,500	1%
7	Colleges, Universities, and Professional Schools, Including Junior Colleges	52,900	3,858,000	1%
8	Banking and Related Activities	43,700	1,962,800	2%
9	Nondepository Credit and Related Activities	43,500	1,169,300	4%
10	Architectural, Engineering, and Related Services	39,900	1,860,500	2%

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

Table 50. Industries Displacing the Most Workers, 2019-2021

Rank, Number of Displaced Workers, U.S.	Census Industry	Number of Displaced Workers, U.S.	Jobs, U.S.	Displacement Rate
1	Restaurants and Other Food Services	351,500	6,747,300	5%
2	Construction (The Cleaning Of Buildings and Dwellings Is Incidental During Construction and Immediately After Construction)	213,100	11,185,900	2%
3	Other Amusement, Gambling, and Recreation Industries	111,700	1,521,900	7%
4	Elementary and Secondary Schools	87,800	9,182,300	1%
5	Computer Systems Design and Related Services	85,200	4,168,900	2%
6	General Medical and Surgical Hospitals, and Specialty (Except Psychiatric and Substance Abuse) Hospitals	74,100	7,214,100	1%
7	Management, Scientific, and Technical Consulting Services	69,500	1,605,900	4%
8	Outpatient Care Centers	69,300	2,092,800	3%
9	Banking and Related Activities	68,000	1,883,800	4%
10	Colleges, Universities, and Professional Schools, Including Junior Colleges	60,500	3,651,300	2%

Note: Excludes industries that are not specified and/or cannot be crosswalked to NAICS.
Source: CPS DWS; Mass Economics analysis.

10. APPENDIX FROM DEVELOPING AN INDUSTRY- BASED APPROACH

10.1 Overview

This document provides a detailed description of the process for developing an industry-based approach to analyzing worker displacement in the Appalachian Region and nationally over the period from 2011 to 2021.

10.2 Data Sources

This task relies on four data sources: Current Population Survey Displaced Worker Supplement (CPS DWS), Quarterly Census of Employment and Wages (QCEW), Quarterly Workforce Indicators (QWI), and the Your-economy Time Series. Below is a brief description of each.

CPS DWS

The 2014-2022 CPS DWS data are used for creating national industry displacement profiles. As in the previous task, CPS data are used as part of the "denominator" for the displacement rates in the analysis.

QCEW

QCEW is a quarterly Bureau of Labor Statistics (BLS) data product that originates from state ES-202 (employment and wage) administrative data. These data track monthly, quarterly, and annual employment and quarterly and annual payroll and establishments at a detailed (6D NAICS) industry level. BLS QCEW provides data down to the county level. data- Fab conducts additional processing on these data to solve suppressed data points. QCEW data are the anchor of the industry mix analysis, providing detailed industry annual employment at the county level.

QWI

QWI is a Census Bureau data product. In addition to providing employment, employment change, and wages by industry, QWI also provides information on worker demographics (e.g., age, race/ethnicity, sex, education) and employer characteristics (e.g., firm age, firm size). The underlying data are derived from the Longitudinal Employer-Household Dynamics (LEHD) microdata, which rely on QCEW, unemployment insurance data, Census Business Dynamics Statistics (BDS), and other sources of information on demographics (e.g., decennial censuses, ACS, others). QWI data are used for the separations and hires method and analysis of displaced worker demographics.

YTS

YTS is a data product developed by the University of Wisconsin's Business Dynamics Research Consortium. Published every year, YTS data capture public and private establishments at the point level (i.e., their more-or-less exact business location), along with information on their industry, sales, and employment. YTS data only reflect the universe of establishments "in business" – that is, those engaging in commercial activity as distinct from entities formed for administrative or tax reasons or otherwise not engaged in commercial activity.

YTS data are used to understand establishment-level dynamics (e.g., moves, closures) over time. YTS data are a time series of point-level establishments, with information over time on industry (NAICS), location (county FIPS code), and jobs. YTS reports information on 24.2 million establishments across the U.S. that are in operation for at least a portion of the period we are studying. (For comparison, in 2021, QCEW captures about 10.6 million private sector establishments nationally.)

10.3 Aligning Census and NAICS Industries

Industry Vintages

The DWS data are reported in Census industries while most other economic industry data use NAICS codes. For the time period of this study (2011-2021), we must crosswalk between two vintages of Census industries in order to arrive at 2017 NAICS. DWS 2014, 2016, and 2018 are reported in 2012 Census industries while DWS 2020 and 2022 are reported in 2017 Census industries.

Crosswalking

We use Census documentation to map 2012 Census industries to 2017 Census industries, then we use Census documentation and Mass Economics crosswalks (with information on industry changes over time) to crosswalk the 2017 Census industries to 2017 NAICS for longitudinal consistency and alignment between data sources.

More specifically, the process involved several steps. We created a universal list of Census industries present in the 2012 and 2017 Census industry universes; tagged whether the code appears in 2012 or 2017; and added in 2012 NAICS and 2017 NAICS definitions and level of industry detail. Then, we assessed whether the definitions are the same in both years (i.e., if the NAICS definition is the same and neither the 2012 nor the 2017 Census industries are crosswalked to a NAICS industry that changed from 2012 to 2017) and determined how to handle the discrepancy (e.g., if the codes needed to be aggregated or split using the Census conversion rate, or no action would be required if the NAICS changed at a more detailed level than the Census industry-to-NAICS industry mapping).

Missing / "Parts of" Census Industries

There are a handful of Census industries that map to "parts" of NAICS industries. Because they show up inconsistently across years and appear at different levels of NAICS detail, they are not included in this analysis. (See Table 51 and Table 52.)

Table 51. Census Industries Missing in the 2012 Census Industry Vintage

Census Industry	Industry Code	Concordance
Not specified type of mining	480	Part of 21
Not specified food industries	1290	Part of 311
Not specified metal industries	2990	Part of 331 and 332
Not specified machinery manufacturing	3290	Part of 333
Not specified manufacturing industries	3990	Part of 31, 32, 33
Not specified wholesale trade	4590	Part of 42
Not specified retail trade	5790	Part of 44, 45
Electric and gas, and other combinations	590	Pts. 2211, 2212
Not specified utilities	690	Part of 22
Executive offices and legislative bodies	9370	92111, 92112, 92114, pt. 92115
Justice, public order, and safety activities	9470	922, pt. 92115

Table 52. Census Industries Missing in the 2017 Census Industry Vintage

Census Industry	Industry Code	Concordance
Not specified type of mining	480	Part of 21
Not specified food industries	1290	Part of 311
Not specified metal industries	2990	Part of 331 and 332
Machinery manufacturing, n.e.c. or not specified	3291	3332, 3334, 3339, Part of 333
Not specified manufacturing industries	3990	Part of 31, 32, 33
Not specified wholesale trade	4590	Part of 42
Not specified retail trade	5790	Part of 44, 45
Electric and gas, and other combinations	590	Pts. 2211, 2212
Not specified utilities	690	Part of 22
Executive offices and legislative bodies	9370	92111, 92112, 92114, pt. 92115
Justice, public order, and safety activities	9470	922, pt. 92115

Comparison to Industry Sector in the Worker Characteristics Method

It is worth noting that the industry sectors used in the worker characteristics method were based on the sector crosswalks listed in CPS documentation while the industry sectors rolled up for the industry mix approach were based on Census documentation (and generally were crosswalked from Census industry to 6-digit NAICS, rather than from Census industry to sector), which may produce slight differences.

10.4 Separations and Hires Approach

The separations and hires method uses QWI data at the county level to create rates of separations and hires in the Appalachian Region and non-Appalachian Region portions (as defined by Appalachian Region and non-Appalachian Region counties) in each of the partials. These ratios are multiplied by the stable employment in the Appalachian Region and non-Appalachian Region shares in each partial. Then, the Appalachian Region share of the sum of these products is used to split observations in DWS. These shares are multiplied by the DWS and CPS weights in order to produce weighted estimates for the Appalachian Region.

Table 53. Separations and Hires Splits, 2011-2013

Partial Geography	Jobs, Appalachian Region	Jobs, Non-Appalachian Region	Sep-Hire Ratio, Appalachian Region	Sep-Hire Ratio, Non-Appalachian Region	New Share, Appalachian Region	New Share, Non-Appalachian Region
Albany, NY	15,600	864,400	0.98	0.97	2%	98%
Allentown, PA	37,100	682,000	1.00	0.95	5%	95%
Athens, GA	5,200	136,100	1.03	0.94	4%	96%
Atlanta, GA	1,372,300	3,972,200	0.93	0.94	26%	74%
Bowling Green, KY	2,200	125,900	0.91	0.93	2%	98%
Canton, OH	12,800	362,900	0.88	0.95	3%	97%
Cincinnati, OH	133,300	2,110,000	0.95	0.96	6%	94%
Greenville, SC	632,500	40,700	0.94	0.96	94%	6%
Harrisburg, PA	16,100	706,000	1.01	0.97	2%	98%
Lexington, KY	27,700	500,500	0.94	0.96	5%	95%
Memphis, TN	12,800	1,281,100	1.00	0.97	1%	99%
Montgomery, AL	36,600	275,800	0.97	0.99	12%	88%
Nashville, TN	22,400	1,751,700	0.93	0.91	1%	99%
New York, NY	19,300	12,849,400	1.00	0.94	0%	100%
Roanoke, VA	24,200	327,400	0.92	0.98	6%	94%
Tuscaloosa, AL	173,000	3,200	0.95	0.90	98%	2%
Washington, DC	31,400	4,816,900	0.95	0.98	1%	99%
Winchester, VA	7,200	111,800	0.96	0.94	6%	94%
Nonmetro Alabama	430,500	428,200	0.97	0.99	50%	50%
Nonmetro Georgia	284,800	797,000	0.96	0.97	26%	74%
Nonmetro Kentucky	588,800	583,600	1.02	0.96	52%	48%
Nonmetro Maryland	26,000	221,200	0.98	0.98	11%	89%
Nonmetro Mississippi	458,100	634,300	0.96	0.99	41%	59%
Nonmetro New York	432,600	618,300	0.99	0.98	41%	59%
Nonmetro North Carolina	442,200	1,416,400	0.98	0.96	24%	76%
Nonmetro Ohio	659,300	1,025,700	0.97	0.95	40%	60%
Nonmetro Pennsylvania	1,324,200	198,500	0.98	0.95	87%	13%
Nonmetro South Carolina	105,600	560,100	0.98	0.96	16%	84%
Nonmetro Tennessee	606,800	413,700	0.96	0.96	60%	40%
Nonmetro Virginia	317,100	405,600	1.03	0.99	45%	55%

Source: dF-QWI; Mass Economics analysis.

Table 54. Separations and Hires Splits, 2013-2015

Partial Geography	Jobs, Appalachian Region	Jobs, Non-Appalachian Region	Sep-Hire Ratio, Appalachian Region	Sep-Hire Ratio, Non-Appalachian Region	New Share, Appalachian Region	New Share, Non-Appalachian Region
Albany, NY	15,700	882,700	0.98	0.98	2%	98%
Allentown, PA	37,300	701,400	1.02	0.98	5%	95%
Athens, GA	4,900	143,300	1.00	0.93	4%	96%
Atlanta, GA	1,464,700	4,209,300	0.92	0.92	26%	74%
Bowling Green, KY	2,300	146,800	0.99	0.94	2%	98%
Canton, OH	14,200	375,000	0.95	0.99	3%	97%
Cincinnati, OH	139,600	2,193,800	0.95	0.96	6%	94%
Columbus, OH	22,200	2,213,500	0.97	0.95	1%	99%
Greenville, SC	790,500	44,600	0.94	0.89	95%	5%
Harrisburg, PA	15,900	720,300	0.98	0.98	2%	98%
Lexington, KY	30,400	519,100	0.87	0.95	5%	95%
Memphis, TN	15,100	1,305,900	0.99	0.98	1%	99%
Montgomery, AL	37,400	279,900	0.95	0.98	12%	88%
Nashville, TN	23,200	1,945,300	0.97	0.91	1%	99%
New York, NY	19,700	14,005,800	0.98	0.94	0%	100%
Roanoke, VA	25,900	338,600	0.96	0.98	7%	93%
Washington, DC	31,100	4,919,100	1.05	0.98	1%	99%
Winchester, VA	7,300	117,100	1.03	0.93	6%	94%
Winston-Salem, NC	493,200	95,000	0.96	0.94	84%	16%
Nonmetro Alabama	436,700	298,000	0.96	1.00	58%	42%
Nonmetro Georgia	297,900	782,000	0.92	0.96	27%	73%
Nonmetro Kentucky	586,300	616,600	1.01	0.98	49%	51%
Nonmetro Maryland	26,000	103,500	1.01	0.99	21%	79%
Nonmetro Mississippi	461,500	643,900	0.99	0.99	42%	58%
Nonmetro New York	430,500	533,000	1.02	1.00	45%	55%
Nonmetro North Carolina	449,300	997,300	0.97	0.97	31%	69%
Nonmetro Ohio	703,800	1,182,400	0.97	0.96	38%	62%
Nonmetro South Carolina	95,400	375,100	0.99	0.98	20%	80%
Nonmetro Tennessee	583,000	357,800	0.96	0.97	62%	38%
Nonmetro Virginia	304,100	386,300	1.04	0.97	46%	54%

Source: dF-QWI; Mass Economics analysis.

Table 55. Separations and Hires Splits, 2015-2017

Partial Geography	Jobs, Appalachian Region	Jobs, Non-Appalachian Region	Sep-Hire Ratio, Appalachian Region	Sep-Hire Ratio, Non-Appalachian Region	New Share, Appalachian Region	New Share, Non-Appalachian Region
Albany, NY	16,300	906,400	0.91	0.97	2%	98%
Allentown, PA	36,200	727,600	1.00	0.95	5%	95%
Athens, GA	5,400	149,700	0.93	0.98	3%	97%
Atlanta, GA	1,555,600	4,469,300	0.93	0.93	26%	74%
Bowling Green, KY	2,300	154,100	0.98	0.96	2%	98%
Canton, OH	14,500	377,800	1.04	0.99	4%	96%
Cincinnati, OH	144,600	2,271,500	0.96	0.96	6%	94%
Columbus, OH	22,900	2,310,700	0.97	0.95	1%	99%
Greenville, SC	826,000	48,200	0.95	0.94	95%	5%
Harrisburg, PA	16,400	712,600	0.97	0.98	2%	98%
Lexington, KY	33,300	540,400	0.92	0.96	6%	94%
Memphis, TN	16,200	1,334,000	0.86	0.97	1%	99%
Montgomery, AL	38,600	285,500	0.98	0.97	12%	88%
Nashville, TN	23,500	2,100,700	0.94	0.92	1%	99%
New York, NY	20,200	14,687,700	0.95	0.94	0%	100%
Roanoke, VA	26,500	341,200	0.96	0.99	7%	93%
Washington, DC	31,200	5,088,000	0.98	0.95	1%	99%
Winchester, VA	7,200	123,600	1.00	0.93	6%	94%
Winston-Salem, NC	513,200	97,800	0.96	0.94	84%	16%
Nonmetro Alabama	448,700	299,100	0.96	0.99	59%	41%
Nonmetro Georgia	319,800	796,100	0.93	0.98	28%	72%
Nonmetro Kentucky	581,800	621,200	1.01	1.00	49%	51%
Nonmetro Maryland	26,100	104,900	0.98	0.98	20%	80%
Nonmetro Mississippi	470,100	648,500	0.97	1.00	41%	59%
Nonmetro New York	421,900	535,400	1.01	0.97	45%	55%
Nonmetro North Carolina	455,300	1,014,400	0.98	0.97	31%	69%
Nonmetro Ohio	715,400	1,210,800	0.99	0.97	37%	63%
Nonmetro South Carolina	97,000	379,100	0.98	0.98	20%	80%
Nonmetro Tennessee	607,200	363,400	0.95	0.98	62%	38%
Nonmetro Virginia	303,800	392,200	1.01	0.97	45%	55%

Source: dF-QWI; Mass Economics analysis.

Table 56. Separations and Hires Splits, 2017-2019

Partial Geography	Jobs, Appalachian Region	Jobs, Non-Appalachian Region	Sep-Hire Ratio, Appalachian Region	Sep-Hire Ratio, Non-Appalachian Region	New Share, Appalachian Region	New Share, Non-Appalachian Region
Albany, NY	17,000	922,600	1.00	1.00	2%	98%
Allentown, PA	36,200	760,200	0.99	0.96	5%	95%
Athens, GA	6,100	152,500	0.92	0.96	4%	96%
Atlanta, GA	1,628,200	4,660,200	0.94	0.96	26%	74%
Bowling Green, KY	2,400	159,400	0.95	0.98	1%	99%
Canton, OH	13,900	380,700	1.03	1.01	4%	96%
Cincinnati, OH	145,900	2,330,500	0.98	0.97	6%	94%
Columbus, OH	23,200	2,397,900	0.98	0.96	1%	99%
Greenville, SC	862,400	48,200	0.96	0.99	95%	5%
Harrisburg, PA	16,700	723,400	0.98	0.96	2%	98%
Lexington, KY	34,200	554,000	0.99	0.98	6%	94%
Memphis, TN	5,600	1,245,900	0.78	0.98	0%	100%
Montgomery, AL	38,900	286,900	1.01	1.00	12%	88%
Nashville, TN	24,500	2,248,600	0.94	0.93	1%	99%
New York, NY	21,000	15,289,400	0.97	0.95	0%	100%
Roanoke, VA	27,300	340,400	0.93	1.01	7%	93%
Washington, DC	31,100	5,275,900	1.04	0.96	1%	99%
Winchester, VA	7,200	130,100	1.04	0.96	6%	94%
Winston-Salem, NC	531,500	100,500	0.96	0.98	84%	16%
Nonmetro Alabama	460,300	299,900	0.97	0.99	60%	40%
Nonmetro Georgia	342,900	802,100	0.96	0.98	29%	71%
Nonmetro Kentucky	584,100	624,400	0.97	0.99	48%	52%
Nonmetro Maryland	26,400	105,700	0.99	0.98	20%	80%
Nonmetro Mississippi	157,800	216,200	0.98	1.01	42%	58%
Nonmetro New York	413,400	545,500	1.02	0.97	44%	56%
Nonmetro North Carolina	465,900	1,023,000	0.99	0.98	31%	69%
Nonmetro Ohio	722,100	1,224,600	0.99	0.99	37%	63%
Nonmetro South Carolina	100,300	382,800	0.99	0.99	21%	79%
Nonmetro Tennessee	625,300	365,800	0.97	1.00	62%	38%
Nonmetro Virginia	300,400	394,500	1.02	0.99	44%	56%

Source: dF-QWI; Mass Economics analysis.

Table 57. Separations and Hires Splits, 2019-2021

Partial Geography	Jobs, Appalachian Region	Jobs, Non-Appalachian Region	Sep-Hire Ratio, Appalachian Region	Sep-Hire Ratio, Non-Appalachian Region	New Share, Appalachian Region	New Share, Non-Appalachian Region
Albany, NY	15,000	883,600	1.08	1.05	2%	98%
Allentown, PA	33,400	755,700	1.05	1.01	4%	96%
Athens, GA	6,300	157,100	0.96	0.96	4%	96%
Atlanta, GA	1,671,000	4,613,400	0.98	1.01	26%	74%
Bowling Green, KY	2,500	159,300	0.90	1.02	1%	99%
Canton, OH	13,000	365,700	1.07	1.07	3%	97%
Cincinnati, OH	143,000	2,295,800	1.00	1.02	6%	94%
Columbus, OH	23,000	2,392,200	1.00	1.00	1%	99%
Greenville, SC	865,400	45,700	1.00	1.08	95%	5%
Harrisburg, PA	16,400	720,800	1.01	1.02	2%	98%
Lexington, KY	32,000	542,900	1.00	1.01	5%	95%
Memphis, TN	00	1,170,400	0.00	1.03	0%	100%
Montgomery, AL	38,200	278,200	1.02	1.02	12%	88%
Nashville, TN	25,200	2,301,100	1.01	0.97	1%	99%
New York, NY	20,100	14,449,200	1.00	1.06	0%	100%
Roanoke, VA	27,600	328,200	1.00	1.05	7%	93%
Washington, DC	29,600	5,182,300	1.02	1.02	1%	99%
Winchester, VA	7,300	132,500	0.99	1.00	5%	95%
Winston-Salem, NC	532,900	100,900	1.01	0.98	84%	16%
Nonmetro Alabama	458,800	293,900	1.00	1.03	60%	40%
Nonmetro Georgia	344,500	799,400	0.99	1.01	30%	70%
Nonmetro Kentucky	577,000	615,300	1.02	1.02	48%	52%
Nonmetro Maryland	25,600	101,800	0.99	1.02	20%	80%
Nonmetro New York	390,200	519,300	1.08	1.06	43%	57%
Nonmetro North Carolina	456,500	1,006,400	1.02	1.02	31%	69%
Nonmetro Ohio	702,100	1,194,000	1.03	1.04	37%	63%
Nonmetro South Carolina	98,300	370,200	1.07	1.04	21%	79%
Nonmetro Tennessee	622,500	358,700	1.00	1.02	63%	37%
Nonmetro Virginia	285,700	380,300	1.06	1.04	43%	57%

Source: dF-QWI; Mass Economics analysis.

10.5 Industry Mix Approach

The industry mix approach applies the national industry displacement rate to the county-level industry data. This approach assumes that every industry in the Appalachian Region has the same displacement rate as the national industry (i.e., the Appalachian Region's share of worker displacement by industry equals its share of the national industry). These industry displacement rates use the same universe of displaced worker as the previous analyses (ages 20+, tenure of at least 3 years at the job from which they were displaced, displaced due to one of the three types of displacement, had last worked in the last three years, and with no chance of recall) and are calculated using the DWIND variable (industry of the job from which the worker was displaced).

Where detailed Census industry displacement rates are not available, we use the sector equivalent; where the sector equivalent is not available, we use the overall total for the survey year.[39] Following the approach of the previous study, we calculate the displacement rate as the number of displaced workers divided by the sum of the number of currently employed workers and the number of displaced workers not currently employed. However, for the overall period, we calculate the displacement rate as the average of displaced workers divided by the average of all workers; this estimate will be higher than the one calculated using the method of the previous study.

It is worth noting that there are some industries that do not have observations for displaced workers not currently employed; given that this is generally a (very) small share of the denominator – on average, <3% for observations with this information – we allowed these industries' displacement rates to be calculated in the same way. This occurs infrequently (affecting about 29% of industries that can be crosswalked to NAICS) and generally only occurs when the number of displaced worker observations is also small.

39. In the 2014, 2016, 2020, and 2022 surveys, sector 55 is missing, so these industries use the overall survey period total.

10.6 Deeper Dive Using YTS Data: Approach and Processing

Closures

Closures are easy to track in YTS data using the "Last Year" variable, which indicates when and whether an establishment has stopped operating.

Moves

Type 1 displacement consists of plant closures and moves. Moves can be tracked nationally and at the county level, at the 6-digit NAICS level using YTS data. We summarize the YTS data at the national, 4-digit NAICS level in order to avoid potential challenges inherent to the data (e.g., NAICS switches at individual establishments year over year). YTS data are reported in 2022 NAICS, which we crosswalk backwards to 2017 NAICS. There are 4, 4-digit NAICS in sector 51 that have to be aggregated due to imperfect alignments between the 2017 and 2022 NAICS: 5111, 5151, 5152, 5191.

We create a county-distance matrix in QGIS on a county database that is longitudinally consistent (i.e., accounts for any naming or geographic changes over time) using Point on Surface to obtain a centrally located point within the polygon (rather than the centroid, which could lie outside of the polygon). Then we use the Haversine formula in Excel to compute mileage ("as the crow flies") between counties.

By definition, plant closures displace 100% of workers, but plant moves could displace any (variable) share of workers, depending on factors such as the move distance, geography and accessibility, and the industry of the displacing employer (and related factors such as job quality, including but not limited to average wage).

We utilize a geometric approach that approximates the share of workers that are displaced with a move of m miles and an assumed maximum commuting distance of r. The overlapping portion of the commuting sheds – shown simply as a perfect circle of radius r – is assumed to be the share of the workforce that is retained between the original and new locations. The share of the workforce that is displaced is 1 – share retained.

Then, we estimate the share of displaced workers at different move distances. Using data from Replica (made available via Axios[40]), it is possible to calculate the distribution of total daily miles traveled per capita. Across 3,112 counties, the average one-way daily miles traveled per capita is 29.7. In most counties (57%), the average one-way daily miles traveled per capita is below 30. Only four counties have average one-way daily miles traveled per capita above 100. Based on these averages, we set the maximum commute distance r to 50 miles For buckets of 10-mile increments, we average the

40. https://www.axios.com/2024/03/24/average-commute-distance-us-map.

overlapping area (= share of workers that are retained) at half-mile intervals within each bucket (i.e., for moves of up to 10 miles, we average the shares calculated at 0.5-mile, 1-mile, 1.5-mile, 2-mile, 2.5-mile, 3-mile, 3.5-mile, 4-mile, 4.5-mile, 5-mile, 5.5-mile, 6-mile, 6.5-mile, 7-mile, 7.5-mile, 8-mile, 8.5-mile, 9-mile, 9.5-mile, and 10-mile radii). (Of course, this simplifies a complex dynamic driven by industry, geographic, accessibility, proximity, and other factors and accounts for no variation in different regions.)

Other approaches that were considered but not ultimately used: simple binary (e.g., if the move is over a certain distance threshold, all workers are displaced); county-specific commute patterns and worker distribution (e.g., assess, census tract-level commute patterns by county and create county-wide summaries on the distribution of workers); probability of worker displacement given the industry of the displacing establishment[41] and that same industry's presence in the original county (e.g., is the worker more or less likely to find a comparable job in the same industry in the same county).

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41. See, e.g., Neffke, Frank, Anne Otto, and Cesar Hidalgo. 2017. "The Mobility of Displaced Workers: How the Local Industry Mix Affects Job Search." https://www.regionalstudies.org/wp-content/uploads/2018/07/NeffkeOttoHidalgo_DisplacedWorkers.pdf.